STATISTICAL ANALYSIS OF THE FOURTH CASE STUDY IN THE REVERSE AUCTION RESEARCH

A Thesis

by

ANEESH MADHAO BHALERAO

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

August 2011

Major Subject: Construction Management

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Approved by:

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	Boong Yeol Ryoo
Committee Members,	Kevin T. Glowacki
Head of Department,	Joseph P. Horlen

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ABSTRACT

Statistical Analysis of the Fourth Case Study in Reverse Auction Research.

(August 2011)

Aneesh Madhao Bhalerao, B. Arch, Visvesvaraya National Institute of Technology

Nagpur

Co-Chairs of Advisory Committee: Dr. John M. Nichols
Dr. Boong Yeol Ryoo

Participating in an auction and winning items by placing bids has been in practice since at least 500 B.C. Auctions have evolved since then and anyone can now participate in one online and buy items ranging from clothes, electronics, automobiles and homes using online auction websites, such as *eBay*. A Reverse Auction varies from the traditional style of Auction where items or services are won by placing successive higher bids until the auction ends. The study of Reverse Auction was first introduced to Texas A&M University in 2004 and continues today, using a SQL based web system.

This current research provides a detailed statistical analysis of the fourth case study in this long running work. This fourth case study involved the participation of five bidders who had no prior experience in Reverse Auctions. A Microsoft Access database system and ASP web based user interface was developed and used to conduct these initial studies. However, due to the limited capability of the Access system to handle more than a limited number of connections or bidders, a Microsoft SQL database and web system was developed in 2006 and has been used in all subsequent studies. Case

studies have involved up to ten participants. The results from the fourth case study show that a Reverse Auction can result in an increase in the average cost of the job to the owner. Also, there is evidence of game play amongst the bidders and against the purchaser that causes their profits to rise as they gain proficiency in the game. This behavior has been termed as ‘tacit collision’, but it is considered a byproduct of the system and not illegal behaviour. This study analyzes the fourth study data to investigate if the behavior termed “tacit collusion” is evident in the bidding data. This analysis is completed by performing a detailed statistical analysis of the bidding data.

Analysis of the profit percentages illustrates the different stages of the game play amongst the bidders. This game play behavior is illustrated by plotting average number of bids to the profit made by each bidder. The data clearly suggests that the players became efficient in their bidding strategy, although some bidders are more efficient than others. This observation negates the common conception that Reverse Auctions will result in lowering average costs for the owners.

The individual data of bidders for bids and profit reveal why some players were able to obtain higher than average results and why the others were not. This study can be taken further by analyzing the patterns of the successful and unsuccessful players to determine what causes them to gain or lose profits.

DEDICATION

This thesis is dedicated to my parents, Mrinalini and Ravi Bhalerao; my brother, Eeshan Bhalerao and lastly my fiancé, Sneha Nayar; without their support and love my education in the US would never have been possible.

ACKNOWLEDGEMENTS

Of all the people I would like to thank, first I want to extend my sincere gratitude to Dr. John Nichols for creating and nurturing my interest in this area of research. Without his support this work would have never turned out the way it did. I would thank my other committee members, Dr. Boong Ryoo and Dr. Kevin Glowacki for their guidance and help throughout the course of this research.

Next, I would like to thank all the previous students who did excellent work in the research of Reverse Auction Bidding. Their work encouraged me to attain a higher level of success.

All my fellow batch mates, friends and colleagues at Texas A&M University, a big thanks to all for making my stay extremely gratifying. Also thanks to all my professors, Department Head and staff at Construction Science for their help and exceptional support throughout my course.

Finally, thanks to my mother and father for their encouragement and to my fiancé for her patience and love.

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CHAPTER I

INTRODUCTION

BACKGROUND

One of the common and widely used method for securing construction jobs today is the hard bid method (or closed bid) (Gregory 2006). The wide success of this method can be attributed to its potent characteristic of being unprejudiced to all the bidders. A deadline is set to submit the bids in person at a pre-decided location and time. Bids submitted earlier than the deadline remain closed and unknown to all players involved, including the owner. The bids are opened only after the deadline is over and only the owner can compare the prices, although at some locations the bid price is published, although without analysis to check the bids correctness this is to some extent meaningless. The owner will award generally the job to the lowest qualified bidder (Gregory 2006). Due to the open nature of this bidding, this system is considered ethical and remains a popular choice amongst the people in construction industry. However, the perceived shortcomings of the hard-bid method have given way in part to other methods of job procurement. Advancement in technology and especially the development of the internet has bought a revolution in almost all old-school methods of life and the construction industry is no exception.

This thesis follows the style of *Adult Education Quarterly*.

The internet has made it possible to bring together buyers and suppliers on a broader scale, eliminating the need for their physical presence in bidding for prospective jobs. The buyers and sellers are also struggling to find the methods to implement the use of internet in the most effective manner in all industries (Jap 2003), including the purchasing of goods and services.

Reverse Auction systems use in the construction industry has been a long debated topic, essentially related to whether the system is ethical, putting aside that issue, the question of interest is whether this system is economically more efficient than hard bids.

In a Reverse Auction the traditional auction system is reversed, instead of the buyer there are prequalified sellers. The operation is typically carried out over the web; where the sellers place bids descending in price and the buyer accepts the lowest bid; either when the time runs out or when no seller is willing to offer a lower price. Goods are bought and sold, and information is exchanged among buyers and sellers in a private (i.e. hosted by a single company) or a public (i.e. with many firms) electronic market place. Reverse auctions previously used extensively in the chemical industry are now being used increasingly for products and services related to day-to-day maintenance, repair and operations requirements (Edward 2004).

The game play difficulty with Reverse Auction is the open nature of the trading, all prices are instantly visible, which provides potential economic advantage to some, but not necessarily the purchaser. Transparency is assured but the competition form from the hard bid is changed, which is at the core of this research interest, is this change economically healthy.

According to OED (Little, Fowler et al. 1973) a market is defined as '*the meeting together of people for the purchase and sale of provisions or livestock, publically exposed, at a fixed time and place; the time of this; also the assembled company, with minimal outside intervention and providing transparency to the hagglers'*. The internet has made it possible to break this concept of a 'market' when the seller and buyers cannot come together at the same place. The idea of Reverse Auction accomplishes this goal; however they are considered unethical and an unconventional form of bid shopping by some contractors. Nichols (2009) considers Reverse Auction systems, when operated by an independent entity of the purchaser, represents an electronic equivalent of a free market. In construction law, Bid Shopping is the practice of revealing a prospective seller's (contractor's) quoted price to other prospective sellers (or contractors) with an intention to lower the cost of the bid. Lowering the cost of a bid would require cost-cutting measures mainly in labor and materials; and hence is thought by some to typically lower the quality of the work performed. Some states have recognized the unfair nature of bid shopping and acknowledged the fact that it would lead to lower quality and loss of professional ethics. There are laws in place to discourage and eliminate the practice of bid shopping.

Guhya (2010) undertook a detailed statistical analysis of the first case study done by van Vleet (2004) and suggested that the overarching game in Reverse Auction is a combined multiplayer game with two sub-games. The α game is a multiplayer game between the bidders with an intention to seek economic advantage over the other bidders. The ω game is the game between the bidder group and the purchaser; however the ω game in reality is a two player game with an intention to maximizing returns of the bidding group (λ player) at the expense of the purchaser (υ player).

The objective of this research is to continue the analysis by Guhya (2010) for the fourth case study, after his initial seminal work on the first case study. A total of fourteen case studies have been completed in this Reverse Auction research. This is the second detailed statistical study of the initial case studies. This study reviews the data from the fourth case study, completed by (Gujarathi 2008), using the analysis techniques and algorithms established by Guhya (2010). The work allows a comparison of the results collected by Gujarathi (2008) and van Vleet (2004). The study goes further by investigating the trends in bidding patterns and observation of tacit collision. The fourth case study, completed by Gujarathi in 2008 using four participants, and is considered to show the probable occurrence of tacit collusion in the Reverse Auction system play. This case study used the Access software developed by Kim (2004). The profit percentage graphs developed from the data showed no learning curve amongst the participants; who had no prior experience in Reverse Auction Bidding, but showed significant game skill to consistently maximize their profits at the start and towards the end of the game. The current research interest in the ongoing study is to investigate the game play.

RESEARCH OBJECTIVES

The research objectives for this study are based on the methods established by Guhya (2010), which are:

1. Establish plots of the bidding data
2. Compare the bidding patterns shown in the plots with time for all bidders
3. Determine if evidence exists in the bidding data to confirm the existence of the ω game and does it represent some form of collusion
4. Compare the returns of the different bidders in the α game to determine if there are any differences in bidding returns and does it represent some form of collusion

GUIDING QUESTIONS

Questions addressed by this study are:

1. What are different learning trends that can be observed from the profit percentages?
2. How different are these learning trends with respect to each other?
3. What causes the sudden increase in average profits? Is this the correct indicator of collusion?
4. Is there a specific player that causes the sudden rise? How can this player be identified?

LIMITATIONS AND DELIMITATIONS

The scope of this study is based on the following factors:

1. All players involved in this game were from the Department of Construction Science, Texas A&M University; faculty and graduate students from the Department of Construction Science acted as the bidders in the game and had no prior experience in Reverse Auction Bidding

2. The study was performed under controlled settings with limited variables that exist in a real business scenario, eliminating most risks involved in business transactions; thus allowing the research learn to focus on the bidding patterns of the bidders
3. The study ignores any clerical errors on part of the bidders, like missing a digit when entering a bid and the legal conflicts that would follow as a result
4. This case study represents a sample size of one; meaning that it constitutes a case study, primarily applicable to the selected population with Herfindahl Index (Justice 2011) of 2500
5. Steady economic conditions were assumed for the study period
6. The data obtained from Gujarathi's (2008) case study will be used in analysis and results compared to data from van Vleet's (2004) initial case study
7. There were some inconsistencies observed in Gujarathi's data (2008), which will be discussed later

SIGNIFICANCE OF THE STUDY

According to Gujarathi (2008), *'It is important to analyze the techniques developed and employed by the bidders during the game which would help to understand the game strategy of the players and allow for a real review of the ethics of the bidding system.'*

van Vleet (2004) also mentioned that *'In order to accurately assess the implications of reverse auctions, it is essential to know and understand the behaviors of those who engage in the bidding process. Without a method of evaluating the process, it* *is impossible to clearly understand whether Reverse Auction Bidding is a success or not'*.

This study attempts to extract the crucial results from Gujarathi's (2008) data using the analysis techniques used by Guhya (2010) to establish the presence of tacit collusion and determine the techniques to prove the same.

CHAPTER II

LITERATURE REVIEW

INTRODUCTION

Fourteen case studies on the Reverse Auction system have been completed at Texas A&M University, this study specifically looks at the case study work by Gujarathi (2008) and attempts to extract the crucial results from Gujarathi's (2008) data using the analysis techniques developed by Guhya (2010). The purpose is to look for the presence of tacit collusion in the bidding system. This chapter presents the definitions, game type and provides a more detailed review of Reverse Auction Bidding system as outlined initially by Chauhan (2009) in terms of game play.

PRIOR STUDIES

A list of some of the previous Reverse Auction Bidding Studies is presented in Table 1.

Table 1 Previous Reverse Auction Bidding Studies

Year	Researcher	Participants	Herfindahl Index	Remarks
2004	van Vleet	5	2000	Competitive
2006	Gregory	10	1000	Very competitive
2008	Chauhan	5	2000	Competitive
2008	Gujarathi	4	2500	Less competitive

THEORETICAL FRAMEWORK USED FOR THE CASE STUDY

The purpose of van Vleet's professional paper was to establish a controlled setting in which a select group of diverse individuals were placed in a controlled and a competitive environment with one undisputed objective: to maximize profits. Using the information from a report posted in Fortune 500 in 1987 for return on investment 10% return on equity was used as a baseline determining factor for evaluating participant performance (Oster 1990; van Vleet 2004).

For the purpose of van Vleet's study, economics of scale were not applied nor were the construction costs changed with a change in the project. Construction delivery methods of project delivery system were also excluded so that there could be no possibility of reducing time for the construction process.

For the purpose of the inline simulation model, the participants, pre-selected for the game, are assumed to be from firms of the similar scale with similar annual revenues so as to avoid the conflicts of interest that may arise between a large and a small firm.

Also, the controlled simulation eliminated the entry of new competitors in the bid and therefore no entry pressures were generated (van Vleet 2004). The importance of these points is that the research is assumed to occur during a stable market period, such as existed in 2004.

DEFINITIONS

The terms used in this study have been previously used and established by, van Vleet (2004), Gregory (2006), Panchal (2007), Chaudary (2009), Chauhan (2009) and

Guhya (2010). This study only outlines the definitions from these previous studies. The definitions are as given below and maintain the exact wording developed by others:

λ player	This represents the bidder group, treated as a single entity for the purpose of game analysis.
λ_i player	The ith bidder in the bidding group.
υ player	This represents the purchaser.
α game	The postulated sub-game played between bidders in seeking economic advantage over the remaining bidders. This game almost always disadvantages the υ player, but the υ player created the system and so is responsible for the υ player's economic losses as a result.
ω game	The postulated sub-game played within the Reverse Auction Bidding game between the purchaser and the bidders. In terms of this analysis, it is deemed to effectively reduce to a two-player game, with competition implications for all players. The υ player in reality sees only the average of all won bids.
τ	Bid time allowed for each round of play in the game.
δ	Period between bid time τ that represents the work time in

the game.

B_j — i^{th} bid

B_v — Accepted bid for each job.

K — This variable is a fixed dollar sum, representing the υ player's base price, although in this game K is a vector of costs.

Γ — This variable is a fixed dollar sum, representing the υ player's maximum incremental price above K.

Ξ — This variable is normally defined by the set of numbers ($\Xi |\ 0 < \Xi \leq 1$), although negative values of Ξ are permitted by the Reverse Auction Bidding system. Ξ is used to normalize the profit data. A negative Ξ_j represents a loss on direct costs to the λ_i player who makes this type of bid, and enough of these bids will lead to a bankrupt player. This type of play is discouraged as the assumption in the game is steady state economic conditions in the outside economy. Future studies may look at a failing market, but that is beyond this study.

Aggressive Bidder: — Willing to accept calculated risk of greater than average loss in pursuit of greater than average returns, first defined by Chouhan (2009).

Bid: A single entry into the game that represents a legally acceptable offer to complete the work assuming the bidder has been prequalified.

Bidder: An entity that submits a bid. In this game, there are usually three to ten bidders, and each is an individual, rather than a company. In van Vleet's (2004) study, none of the bidders had prior experience, which is not true for Chauhan's (2009) study.

Bid Efficiency: Is the ratio of the total number of jobs won to the total number of bids. This is one of the postulated metrics for determining success in the α game.

Case Study: '*Designed to study intensely one set (or unit) of something; for e.g. programs, cities, counties, worksites- as a distinct whole, with the goal of understanding the set as a distinct whole in its particular context. A case study reveals the process and outcome at certain sites and the way in which these interrelate. Case studies are conducted primarily using qualitative techniques, but do not exclude*

	quantitative data (van Vleet 2004)'.
Collusion:	*A secret agreement between two or more parties for a fraudulent, illegal or deceitful purpose (van Vleet 2004).* Or as defined by the Oxford English Dictionary (Little, Fowler et al. 1973) as '*secret agreement or understanding for the purpose of trickery or fraud*' is generally considered to be reprehensible and is usually illegal in a free market system, because of the economic distortions introduced into the market.
Dutch Auction:	*is a type of auction where the auctioneer begins with a high asking price which is lowered until some participant is willing to accept the auctioneer's price, or a predetermined reserve price (the seller's minimum acceptable price) is reached (van Vleet 2004).*
Economic Winner:	*An individual who generated the highest average returns.* Panchal (2007) coined this term to indicate a more successful player in the α game. An economic winner makes no direct difference to the ω game for the υ player where the υ player has an objective of minimizing the average bid for the game. The υ player sees the average

price for purchases and a distribution of prices.

Economic Loser*:* *An individual who generated the lowest average returns.* Panchal (2007) coined this term to indicate a less successful player in the α game. An economic loser makes no direct difference to the ω game for the υ player where the υ player has an objective of minimizing the average bid for the game.

Efficiency: The ratio of the output to the input of any system.

Game: A series of jobs for the construction of a reinforced concrete floor slab, each game lasts approximately 8 to 10 weeks in game play time, with each round of the game modeling a week and occurring in a 20 minute period, with 15 minutes of bid time and 5 minutes of build time.

Game theory: A formal analysis of conflict and cooperation among intelligent and rational decision makers.

Job: A work unit, in this case a reinforced concrete slab for a home builder, taking 5 working days to construct.

Loan amount: It is a bank loan or a guarantee taken by the bidder with the purpose of increasing the bidders' job capacity. The cost is $500 per job.

Loss: Negative return applied to a business undertaking after all operating expenses have been met.

Lump Sum offer: A tender submitted for a lump sum amount in the game assumed to be for a fixed price.

Pre-Qualified: The process of declaring competent or capable or to certify in advance. The purpose of prequalified is to maintain the economic competition.

Profit: The return received on a business undertaking after all operating expenses have been met.

Profit Efficiency: It is the ratio of the profit made to the number of jobs won. This is one of the postulated metrics for determining success in the α game.

Purchaser: Either an owner or owner's representative who organizes the bid or tender document.

Reverse Auction Bidding: *It is a single or multiple-item, open, descending-price auction. The initiator specifies the opening bid price and bid decrement. Each bidder submits a successively lower bid. At the end of the auction, the bidder with lowest bid*

	value is being considered as a winner (van Vleet 2004).
Second Bidder Issue:	*It has been postulated that the lowest bidder in Reverse Auction Bidding is seeking to undercut the second bidder by the smallest quantifiable fragment, if the bidder understands the principles of tacit collusion (Chaudary 2009).* The hypothesis forms the basis for future research.
Sealed Bidding:	*In this type of auction, all bidders simultaneously submit bids in such a way that no bidder knows the bid of any other participant. The highest/lowest bidder is awarded the contract at an agreed price, all other things being equal .(van Vleet 2004).*
Sherman Antitrust Act:	*The act, based on the constitutional power of Congress to regulate interstate commerce, declared illegal every contract, combination (in the form of trust or otherwise), or conspiracy in restraint of interstate and foreign trade.* According to Nichols (2010), *the problem is tacit collusion does not fit within the meanings of the act, thus leading to the debate about the legality of RAB between contractors who consider it illegal or unethical and economists who accept the converse.*

Tacit Collusion: *Seemingly independent, but parallel actions among competing firms (mostly oligopolistic firms) in an industry that achieve higher prices and profits, much as if guided by an explicit collusion agreement. Also termed implicit collusion, the distinguishing feature of tacit collusion is the lack of any explicit agreement. The key is that each firm seems to be acting independently, perhaps each responding to the same market conditions, but the end result is the same as an explicit agreement. This should be contrasted with explicit or overt collusion that does involve a formal, explicit agreement. Tacit collusion is observed in Reverse Auction Bidding, and is potentially related to the Second Bidder Issue (Chauhan 2009).* Nichols (2010) postulates that the α game has been observed and misunderstood as tacit collusion, in reality it can be viewed potentially reviewed as an aggressive player seeking a better than average return from the profit distribution resulting from the α game.

Traditional bidding: *In this type of auction all bidders simultaneously submit bids in such a way that no bidder knows the bid of any other participant. The highest/lowest bidder is assumed to* *be awarded at the price submitted provided no other contracts opened on the decision process* (Chaudary 2009).

Winners Curse: *Problem faced by uninformed bidders or poor game players. For example, in an initial public offering uninformed participants are likely to purchase larger allotments of issues that informed participants know are overpriced.*

GAME TYPE

Consider a Reverse Auction Bidding game where the υ player is willing to accept bids of the type shown in equation (1):

$$B_j = \mathrm{K} + \Xi_j \, \Gamma \qquad (1)$$

Γ represents the upper limit the υ player is prepared to pay in the game above the nominal minimum bid amount K. A negative Ξ_j represents a loss on direct costs to the λ_i player who makes this type of bid, and enough of these bids will lead to a bankrupt player (Guhya 2010). The concept of Γ can be attributed to Feigenbaum (Nichols 2010), who considered there had to be an upper limit everyone was prepared to pay for a service or good, the so called price point of economic theory.

The bidding period for each game lasts for a set time, τ, in this case it is 15 minutes. The total cost for υ player is shown in equation (2):

$$B_\upsilon = \sum_{j=1}^{n} B_j, \quad (2)$$

This total cost is based on the accepted lowest bid for each job, where the λ_i player submitted a valid bid for a job. Each λ_i player then has a unique set of bids and a unique set of jobs, with a total return to the λ_i player defined by a simple summation (Guhya 2010). In terms of the υ player, the average cost per job and the total cost are the main elements. The lowest and highest costs are of interest, but the υ player's clear objective must be to lower the average price. This is not necessarily the key objective of the other players, who seek economic advantage in a range of costs.

REVERSE AUCTION BIDDING – THE GAME

The Reverse Auction game played by Gujarathi (2008) follows the same rules established by the game played by van Vleet (2004) with the only difference in the number of players from 5 (van Vleet) to 4 (Gujarathi). The Herfindahl Index in case of van Vleet was 2000 whereas in Gujarathi's case study was 2500, which indicates a less competitive market and a higher chance of collusion, making this an ideal vehicle to study tacit collusion.

Herfindahl Index (HHI) is a commonly accepted measure of market concentration. It is calculated by squaring the market share of each firm competing in the market and then summing the resulting numbers. Markets in which the HHI is between 1000 and 1800 points are considered to be moderately concentrated and those in which the HHI is in excess of 1800 points are considered to be concentrated (Justice 2011). Figure 1 shows the ideal steps to be undertaken to execute a successful reverse auction.

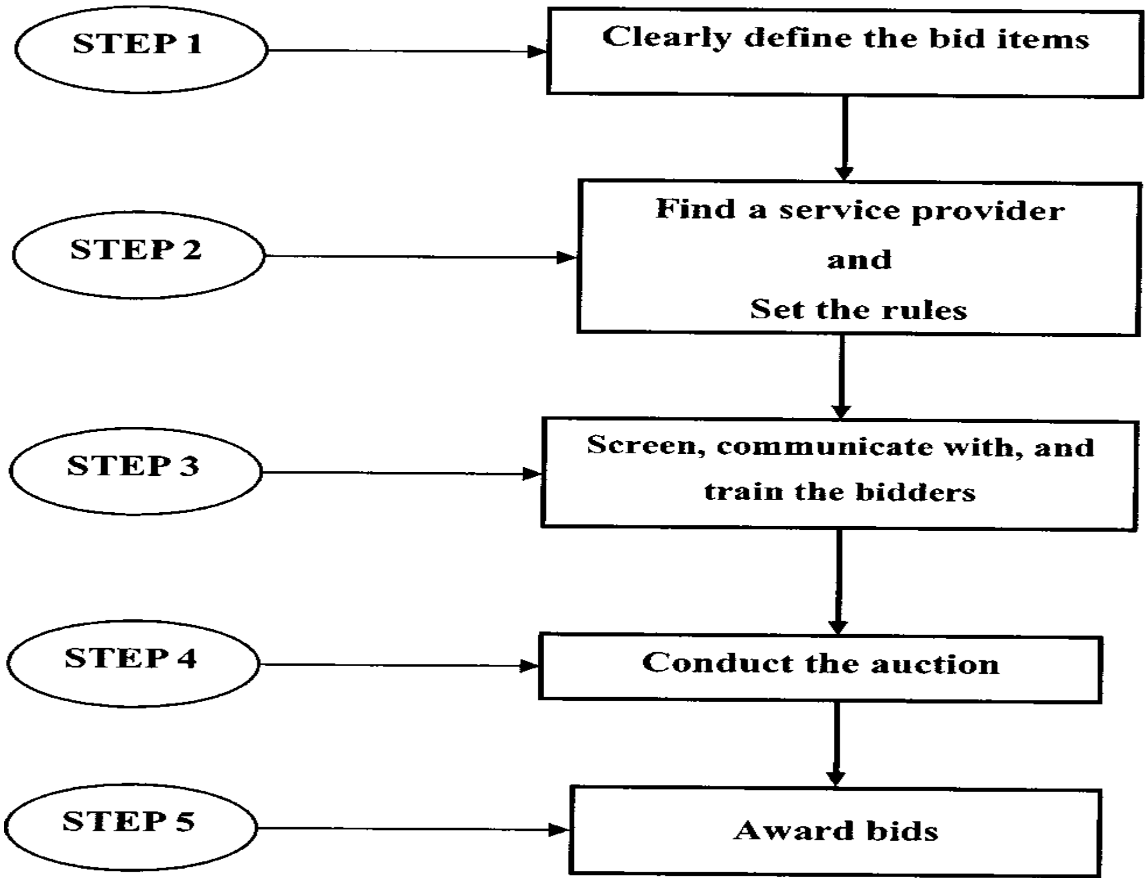


Figure 1 Recommended Steps for a Successful Reverse Auction (Chaudary, 2009)

For the scope of the study Step 4 in Figure 1 was executed using a web based data system. This was done using the website and game scenario developed by van Vleet in 2004. Microsoft Access and ASP Programming were used to connect a database to the website which would provide information to the participants and also record their data. The typical process of running a game was summarized by Guhya (2010) and is given in Figure 2. The process continues until time allotted for a game (15 minutes in Gujarathi's case) runs out. This time frame of 15 minutes is established for practical reasons of conducting research, which otherwise represents a full week in a real life scenario in the game.

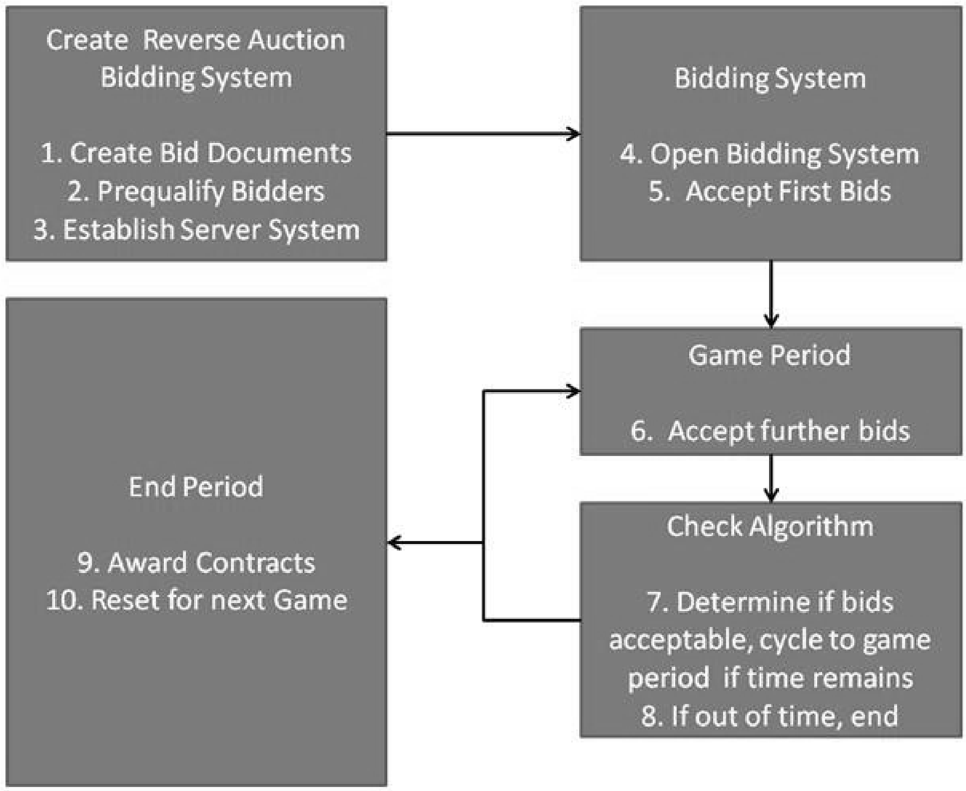


Figure 2 Reverse Auction Bidding General Algorithm (Guhya 2010)

The game scenario developed by van Vleet is described below.

- The bidders were assigned an individual login and password that enabled them to login to the website.
- Once logged in, the bidders were able to access only relevant information to the bidding process.

- Four login names were created, Driver, Concrete, Hammer and Pliers, each were assigned a unique bidder id from one to four and given a unique password. Figure 3 shows the login page of the website.

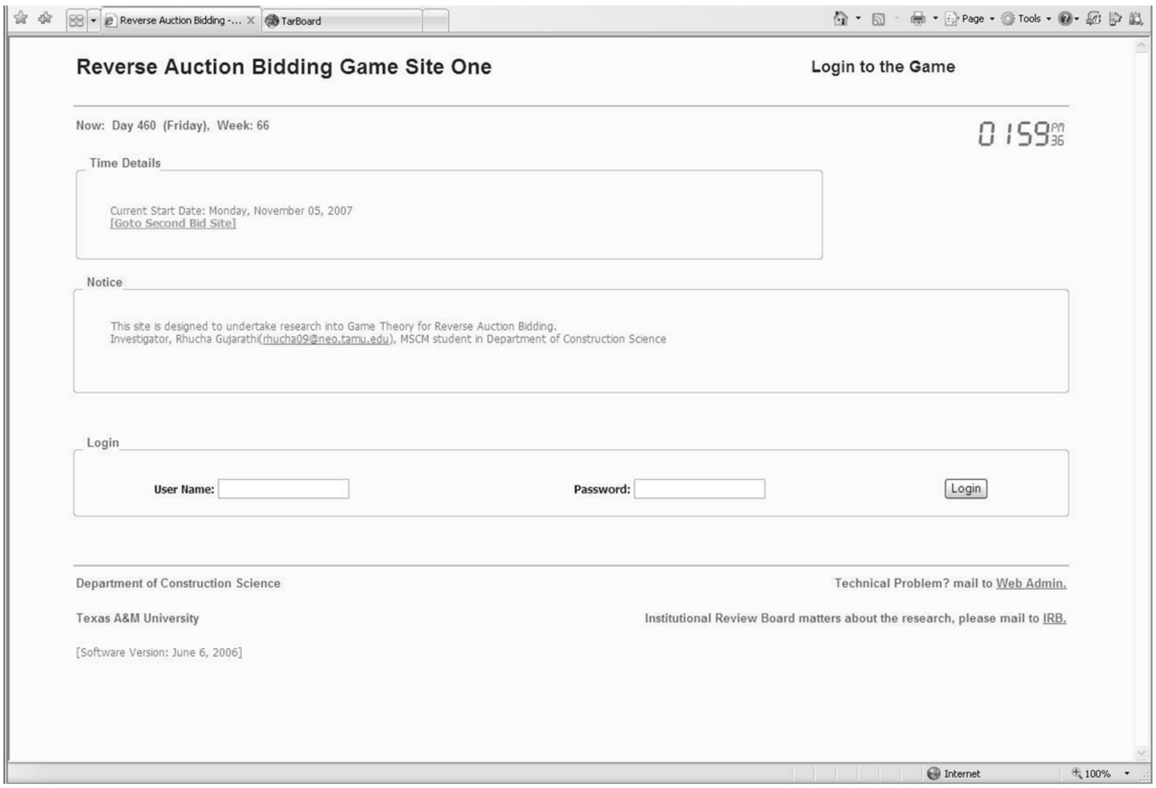


Figure 3 Login Screen

All construction sites were selected in the Houston area as shown in Figure 4. Each job site was assigned a unique site ID. To ensure that each job site was represented in the entire simulation process, two dice were rolled to determine the number of jobs in a week. Thus the minimum number of jobs possible were two and maximum possible were twelve.

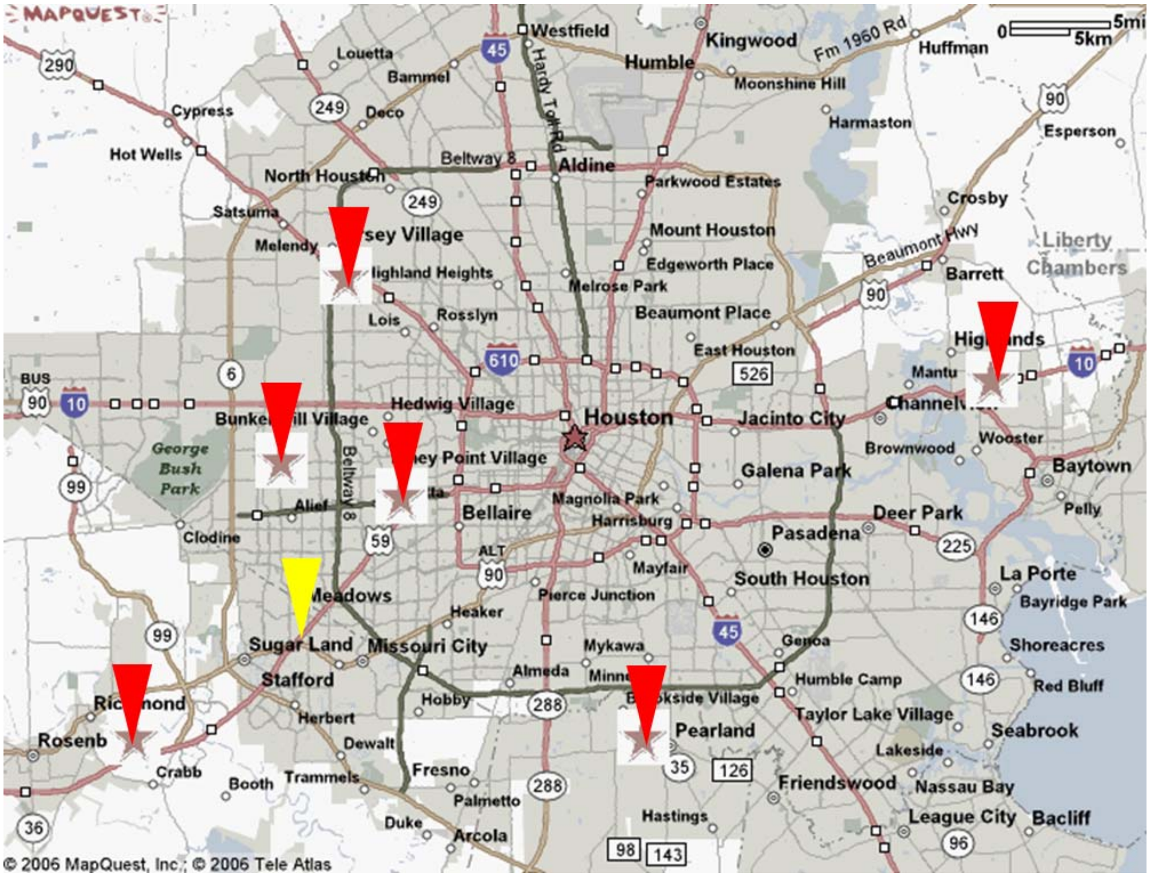


Figure 4 Locations of Construction Sites in Houston (MapQuest 2006)

The purchaser's office was assumed to be located in Sugarland, TX. Thus each job site was assured to have different travel and delivery costs associated. These costs were assumed to be directly proportional to the proximity of the job site to the purchaser's office. Thus the further the job site from the purchaser's office, the higher would be the travel and delivery costs. The assumption made by van Vleet is that the subcontractors would be located close to the contractor. This is a research assumption for developing a game such as for this study. Alternative assumptions could be made in further studies.

For the purpose of the game, these costs were notified to the bidders along with the base cost of the project. Table 2 displays the location of sites with their associated costs.

Table 2 Construction Site Locations, Travel and Material Costs

Site Number	**Location of Development**	**Distance from Sugarland (kilometers)**	**Cost of Travel ($)**	**Cost of Material Delivery ($)**	**Total Cost ($)**
1	Brookside Village	42	858	624	1482
2	Piney Point Village	24	495	360	855
3	Highlands	71	1452	1056	2508
4	Jersey Village	40	825	600	1425
5	Bunker Hill Village	27	561	408	969
6	Richmond	14	297	216	513

To introduce variability in the auction, rain delay is introduced to the game. Data obtained from a NOAA website shows the rain probability in the Houston area between the months of May and June. This is the time of the year selected by van Vleet for his model game.

Gujarathi (2008), based on the NOAA data, assumed 27% chances of rain per day and used a randomly generated data table from Excel to determine whether it was a rain day or non-rain day on a particular site. Table 3 shows the rain and non-rain days in week 1 for all sites. Similar tables were used for all weeks.

Table 3 Rain Data for Week 1

Day	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6
Monday	1	0	0	0	1	0
Tuesday	0	1	1	0	0	0
Wednesday	0	0	0	0	0	0
Thursday	0	0	1	0	0	1
Friday	1	0	0	0	1	1
Saturday	0	0	0	0	0	0
Sunday	0	1	0	1	0	0

In Table 3, *0* represents no delay by rain and *1* represents delay of one day due to rain. The idea of rain delay mainly had an effect on the work capacity of the bidder. A delay of one day did not cause any change in bid capacity as the time for completion was five days and the work week was six days. However a two day delay in a week meant that the job would be rolled over to the other week, thus reducing the bidder's bid capacity by one for bidding jobs in the next week. This accounted for some of the real life contingencies in a real project scenario.

The rules of the game are:

1. The purchaser builds only one type of home and each job is to pour only one type of slab. Thus the nominal costs for the jobs are same except the travel and delivery costs.
2. All bidders are pre-qualified and hence only the final price matters, as in a real auction.
3. The purchaser posts the available jobs for the week on Monday.
4. Each bidder has $30,000 in their bank account at the start.
5. Base cost of every job is $10,000 excluding the travel and material delivery costs, which are posted on the website.
6. The maximum game duration is 8 weeks, which corresponds to 2 hours 40 minutes in real time; however fatigue in players often limited the games to less than 8 weeks.
7. Each bidder has a capacity to work 3 jobs every week. If the bidder bids for any further jobs, finance charges of $500 are charged by the bank irrespective of whether the bidder wins that job or not.
8. Time required to complete each job is 5 days.
9. The work week is 6 days long (Monday to Saturday) and no work can be done on Sunday.

10. The average return on investment is assumed to be 10% (derived from long term construction industry standards).
11. The construction costs are accrued daily ie. $2,000 per day for a job of $10,000. The bidder does not get paid if the crew does not work on a rain day.
12. The bidder cannot increase his resources (crew and equipment) to increase the rate of work on job site to compensate for lost days.
13. Chances of rain are assumed to be 27% throughout the duration of the game.
14. For practical purposes, a 20 minute game period counts for one week in real life. 15 minutes for bidding and 5 minutes for construction, although the 5 minutes is a break for the players.

Once the bidder was logged in, the website showed a list of currently available jobs open for bidding as shown on Figure 5.

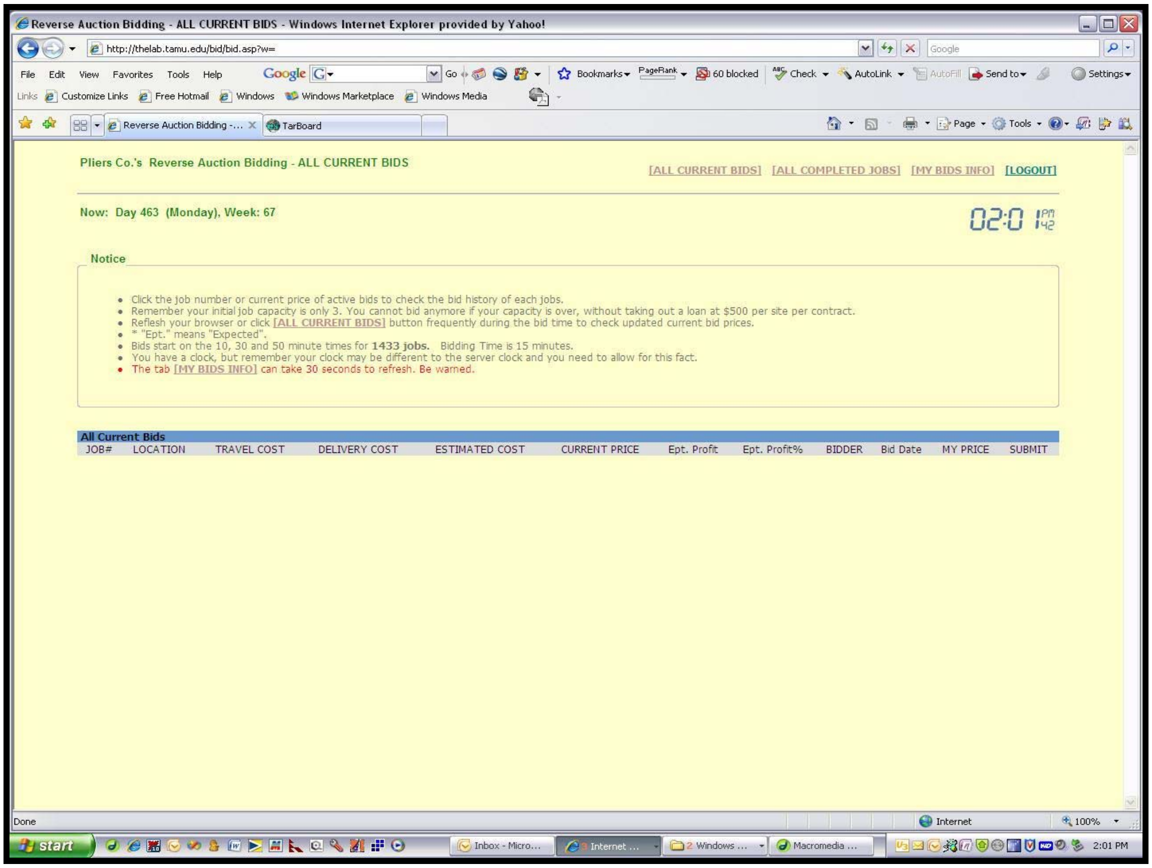


Figure 5 ‘All Current Bids’ Page - Screenshot

In order to place a bid, a text box with a ‘submit’ button was visible on the right side of the screen. The website was programmed to reject any flawed bids, like bids higher than the current bid or bids higher than the remaining financial capacity of the bidder. Once the bid was placed, the profit and profit percentage was visible to the bidder. To maintain anonymity, the other bidders’ names appeared as anonymous place names when they made each bid. The bidders had to constantly ‘refresh’ the page to keep up with the current bids. This is one problem with web based systems.

Figure 6 shows a screenshot of the 'My Bids Info' page. This screen shows the financial state of the bidder, a current under-construction projects and list of previously completed jobs.

If the bidder was outbid for a particular job, this information could be seen under 'My Active Bids'. 'My Jobs in Progress' bar displayed current information about the jobs won by the bidder. It gave information about the job number, location, awarded price, current construction status, any rain delays, and overall cost to date.

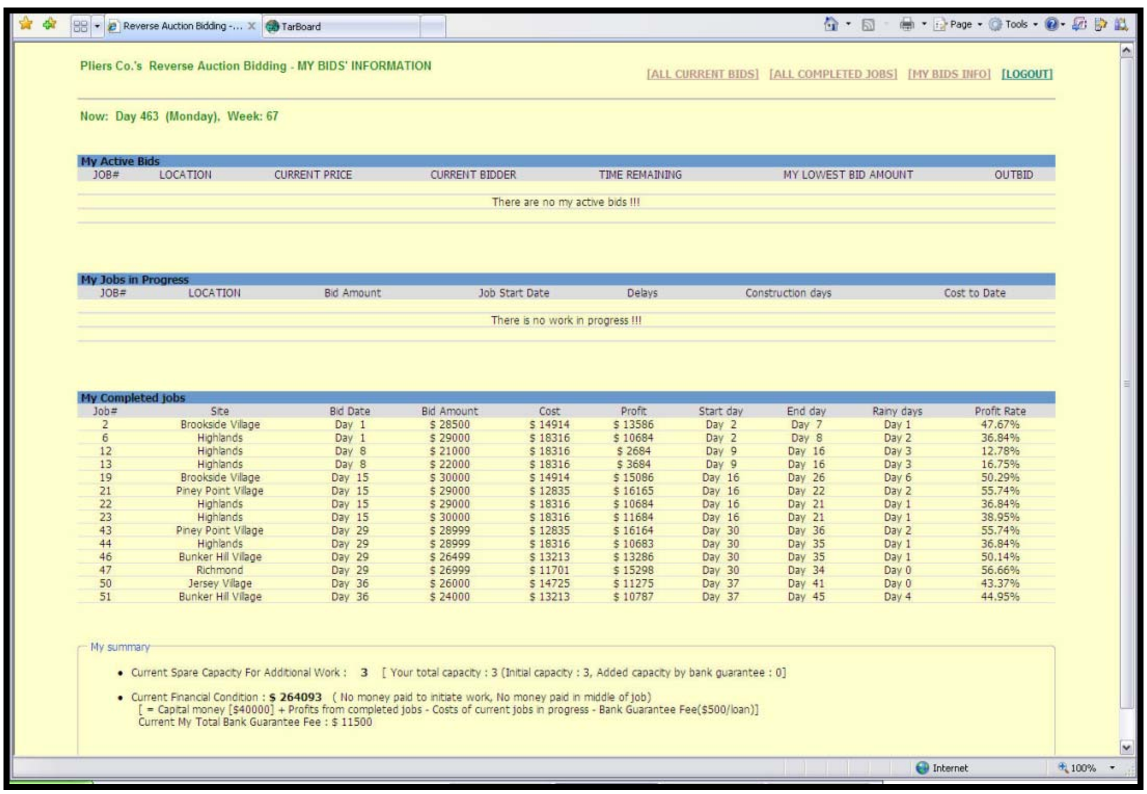
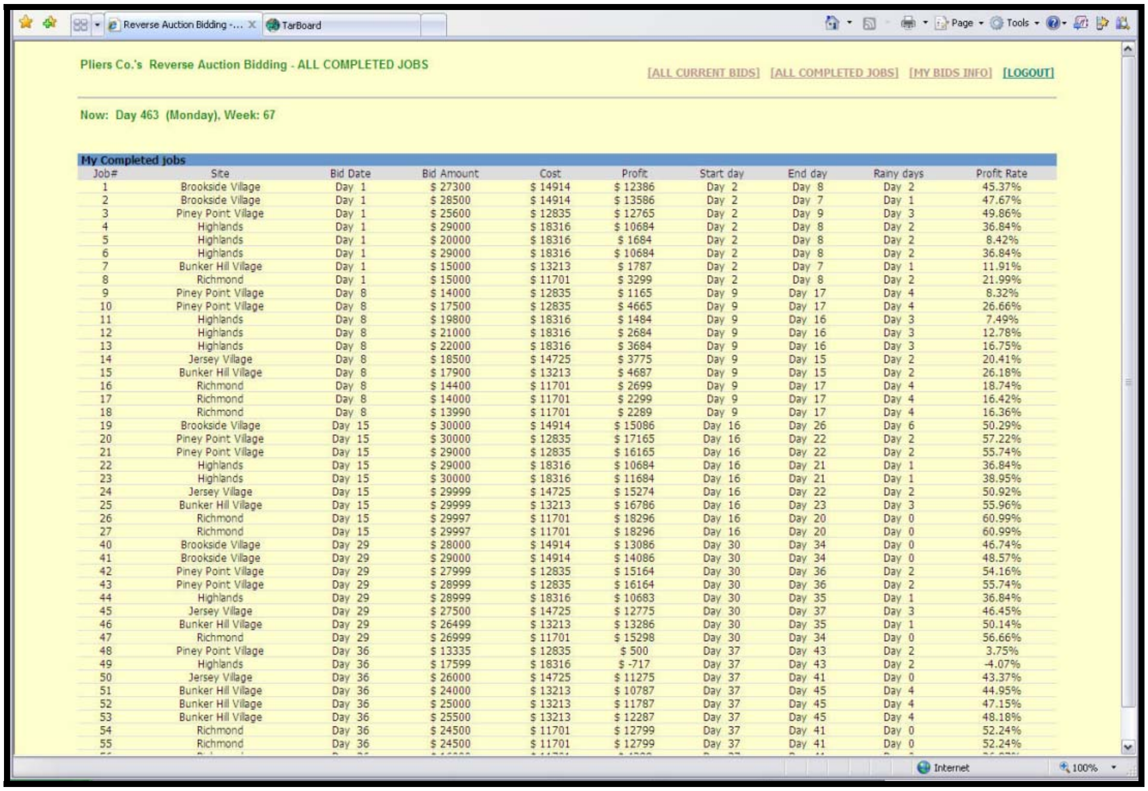


Figure 6 'My Bids Info' Page - Screenshot

'My Completed Jobs' bar (Figure 7) showed the history of work performed by individual bidders. This page helps bidders to prepare their strategy for the next bids.



Pliers Co.'s Reverse Auction Bidding - ALL COMPLETED JOBS

[ALL CURRENT BIDS] [ALL COMPLETED JOBS] [MY BIDS INFO] [LOGOUT]

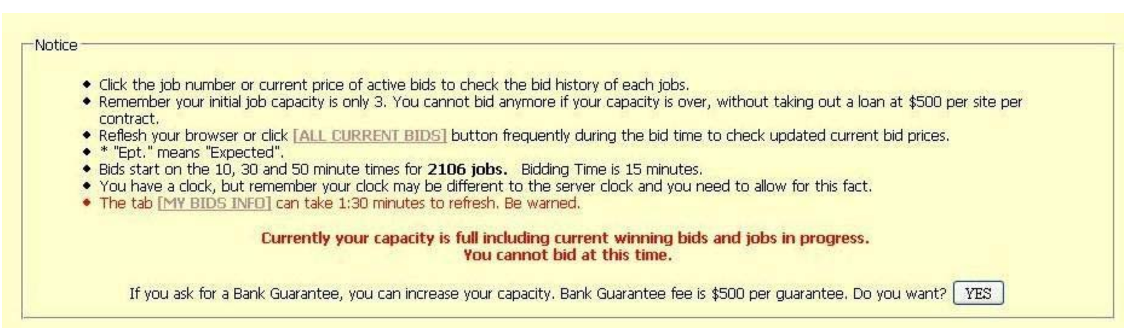
Now: Day 463 (Monday), Week: 67

My Completed jobs

Job#	Site	Bid Date	Bid Amount	Cost	Profit	Start day	End day	Rainy days	Profit Rate
1	Brookside Village	Day 1	$ 27300	$ 14914	$ 12386	Day 2	Day 8	Day 2	45.37%
2	Brookside Village	Day 1	$ 28500	$ 14914	$ 13586	Day 2	Day 7	Day 1	47.67%
3	Piney Point Village	Day 1	$ 25600	$ 12835	$ 12765	Day 2	Day 9	Day 3	49.86%
4	Highlands	Day 1	$ 29000	$ 18316	$ 10684	Day 2	Day 8	Day 2	36.84%
5	Highlands	Day 1	$ 20000	$ 18316	$ 1684	Day 2	Day 8	Day 2	8.42%
6	Highlands	Day 1	$ 29000	$ 18316	$ 10684	Day 2	Day 8	Day 2	36.84%
7	Bunker Hill Village	Day 1	$ 15000	$ 13213	$ 1787	Day 2	Day 7	Day 1	11.91%
8	Richmond	Day 1	$ 15000	$ 11701	$ 3299	Day 2	Day 8	Day 2	21.99%
9	Piney Point Village	Day 8	$ 14000	$ 12835	$ 1165	Day 9	Day 17	Day 4	8.32%
10	Piney Point Village	Day 8	$ 17500	$ 12835	$ 4665	Day 9	Day 17	Day 4	26.66%
11	Highlands	Day 8	$ 19800	$ 18316	$ 1484	Day 9	Day 16	Day 3	7.49%
12	Highlands	Day 8	$ 21000	$ 18316	$ 2684	Day 9	Day 16	Day 3	12.78%
13	Highlands	Day 8	$ 22000	$ 18316	$ 3684	Day 9	Day 16	Day 3	16.75%
14	Jersey Village	Day 8	$ 18500	$ 14725	$ 3775	Day 9	Day 15	Day 2	20.41%
15	Bunker Hill Village	Day 8	$ 17900	$ 13213	$ 4687	Day 9	Day 15	Day 2	26.18%
16	Richmond	Day 8	$ 14400	$ 11701	$ 2699	Day 9	Day 17	Day 4	18.74%
17	Richmond	Day 8	$ 14000	$ 11701	$ 2299	Day 9	Day 17	Day 4	16.42%
18	Richmond	Day 8	$ 13990	$ 11701	$ 2289	Day 9	Day 17	Day 4	16.36%
19	Brookside Village	Day 15	$ 30000	$ 14914	$ 15086	Day 16	Day 26	Day 6	50.29%
20	Piney Point Village	Day 15	$ 30000	$ 12835	$ 17165	Day 16	Day 22	Day 2	57.22%
21	Piney Point Village	Day 15	$ 29000	$ 12835	$ 16165	Day 16	Day 22	Day 2	55.74%
22	Highlands	Day 15	$ 29000	$ 18316	$ 10684	Day 16	Day 21	Day 1	36.84%
23	Highlands	Day 15	$ 30000	$ 18316	$ 11684	Day 16	Day 21	Day 1	38.95%
24	Jersey Village	Day 15	$ 29999	$ 14725	$ 15274	Day 16	Day 22	Day 2	50.92%
25	Bunker Hill Village	Day 15	$ 29999	$ 13213	$ 16786	Day 16	Day 23	Day 3	55.96%
26	Richmond	Day 15	$ 29997	$ 11701	$ 18296	Day 16	Day 20	Day 0	60.99%
27	Richmond	Day 15	$ 29997	$ 11701	$ 18296	Day 16	Day 20	Day 0	60.99%
40	Brookside Village	Day 29	$ 28000	$ 14914	$ 13086	Day 30	Day 34	Day 0	46.74%
41	Brookside Village	Day 29	$ 29000	$ 14914	$ 14086	Day 30	Day 34	Day 0	48.57%
42	Piney Point Village	Day 29	$ 27999	$ 12835	$ 15164	Day 30	Day 36	Day 2	54.16%
43	Piney Point Village	Day 29	$ 28999	$ 12835	$ 16164	Day 30	Day 36	Day 2	55.74%
44	Highlands	Day 29	$ 28999	$ 18316	$ 10683	Day 30	Day 35	Day 1	36.84%
45	Jersey Village	Day 29	$ 27500	$ 14725	$ 12775	Day 30	Day 37	Day 3	46.45%
46	Bunker Hill Village	Day 29	$ 26499	$ 13213	$ 13286	Day 30	Day 35	Day 1	50.14%
47	Richmond	Day 29	$ 26999	$ 11701	$ 15298	Day 30	Day 34	Day 0	56.66%
48	Piney Point Village	Day 36	$ 13335	$ 12835	$ 500	Day 37	Day 43	Day 2	3.75%
49	Highlands	Day 36	$ 17599	$ 18316	$ -717	Day 37	Day 43	Day 2	-4.07%
50	Jersey Village	Day 36	$ 26000	$ 14725	$ 11275	Day 37	Day 41	Day 0	43.37%
51	Bunker Hill Village	Day 36	$ 24000	$ 13213	$ 10787	Day 37	Day 45	Day 4	44.95%
52	Bunker Hill Village	Day 36	$ 25000	$ 13213	$ 11787	Day 37	Day 45	Day 4	47.15%
53	Bunker Hill Village	Day 36	$ 25500	$ 13213	$ 12287	Day 37	Day 45	Day 4	48.18%
54	Richmond	Day 36	$ 24500	$ 11701	$ 12799	Day 37	Day 41	Day 0	52.24%
55	Richmond	Day 36	$ 24500	$ 11701	$ 12799	Day 37	Day 41	Day 0	52.24%

Figure 7 'Completed Jobs' Page - Screenshot

When a bidder wanted to bid beyond his work capacity, the screen shown in Figure 8 would caution the bidder and would let him place the bid but pay $500 as finance charges.



Notice

- Click the job number or current price of active bids to check the bid history of each jobs.
- Remember your initial job capacity is only 3. You cannot bid anymore if your capacity is over, without taking out a loan at $500 per site per contract.
- Reflesh your browser or click [ALL CURRENT BIDS] button frequently during the bid time to check updated current bid prices.
- * "Ept." means "Expected".
- Bids start on the 10, 30 and 50 minute times for **2106 jobs.** Bidding Time is 15 minutes.
- You have a clock, but remember your clock may be different to the server clock and you need to allow for this fact.
- The tab [MY BIDS INFO] can take 1:30 minutes to refresh. Be warned.

Currently your capacity is full including current winning bids and jobs in progress.
You cannot bid at this time.

If you ask for a Bank Guarantee, you can increase your capacity. Bank Guarantee fee is $500 per guarantee. Do you want? YES

Figure 8 'Bank Guarantee' Page - Screenshot

By error, if any bidder tried to place a bid that was higher than the current bid, the website would not allow that and would display the message shown in Figure 9.

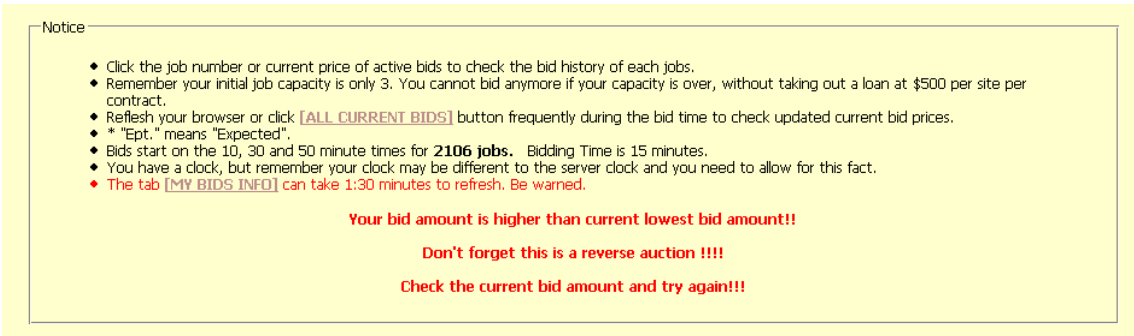


Figure 9 ‘Higher Bid Price Warning’ Page - Screenshot

The game was designed to be played for 8 weeks, however in Gujarathi’s (2008) case, the bidders were fatigued by week 5 and the game was abandoned.

CHAPTER III

METHODOLOGY

INTRODUCTION

This chapter outlines the original case study procedures done by Gujarathi in 2008. All Reverse Auction studies done at Texas A&M University follow common basic study methods, data collection and initial analysis. Guhya (2010) developed further techniques for looking at the statistical properties of the game play.

DISTINCTIVE ELEMENTS TO THE ORIGINAL STUDY

The number of players and distribution of number of jobs in each week in the Reverse Auction game make all the difference in a study. Whilst all the studies in Reverse Auction system have maintained similar characteristics, the main distinctive features in all are the two factors mentioned above.

In order to avoid any bias and maintain equal probability, the available number of jobs in every week is determined using a roll of two or three dice depending on the number of participants. Gujarathi's (2008) case study had four bidders, hence twelve jobs could be worked on each week. With rolling two dice, the number of jobs per week varies from two to twelve. Thus when the number of jobs in a week is less than twelve, the competition amongst the bidders comes into play. This can also be explained by the Herfindahl Index of 2500 with four participants.

The Department of Justice considers a value above 1800 to be concentrated and value in this study is not too far from that. This difference is also be compensated by all participants with equal capacity and offering limited number of jobs. With a three die roll, there are 216 possible outcomes with the value ranging from 3 to 18. Each of the sixteen values ranging from 3 to 18 were plotted by Guhya (2010) against the Gaussian distribution, the resemblance was striking with minor differences which can be ignored for the purpose of the study as shown in Figure 10. A similar graph exists for two die or four.

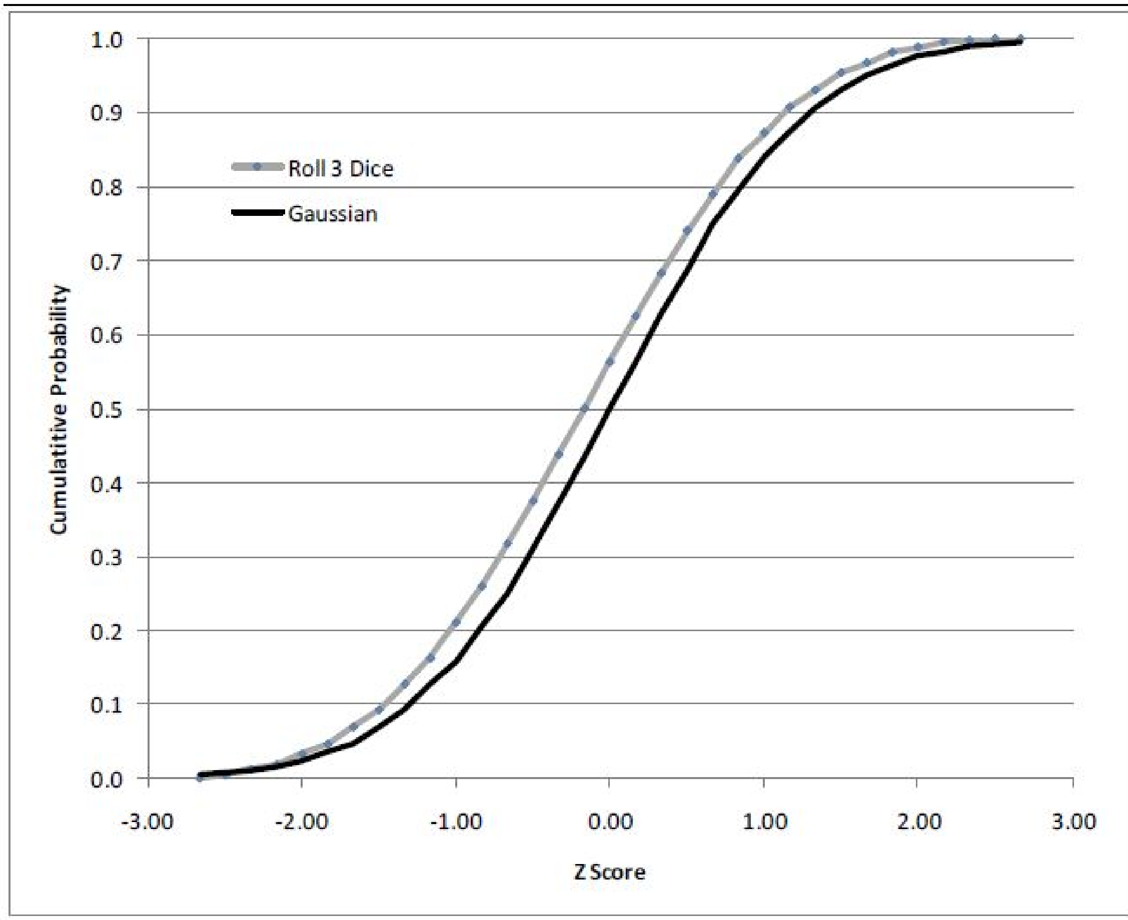


Figure 10 Gaussian Distribution Against Job Distribution Probability per Week (Guhya 2010)

The number of jobs per week is shown in Table 4.

Table 4 Number of Jobs per Week

	Total Jobs	Jobs Bid
Week 1	8	8
Week 2	10	10
Week 3	9	9
Week 4	9	9
Week 5	9	9
Week 6	12	-
Week 7	9	-
Week 8	11	-
Mean	9.63	9.00
Standard deviation	1.22	0.63
Total	77	45

Although a total of 77 jobs were available, the game was abandoned after a five week period corresponding to one hour forty minutes in real time. Hence the data is limited to the bidding that took place on 45 jobs and five weeks.

All four participants that participated in the study were graduate students. The game rules and their individual login id and password were given to them in advance. They were located in different rooms to eliminate any chances of discussion and direct collusion.

The game lasted for one hour forty minutes resembling five weeks of construction time. The total number of jobs bid on was 45 and 346 bids were recorded on the Microsoft Access database. The distribution of profits made on all jobs gives some interesting insight as seen in Figure 11.

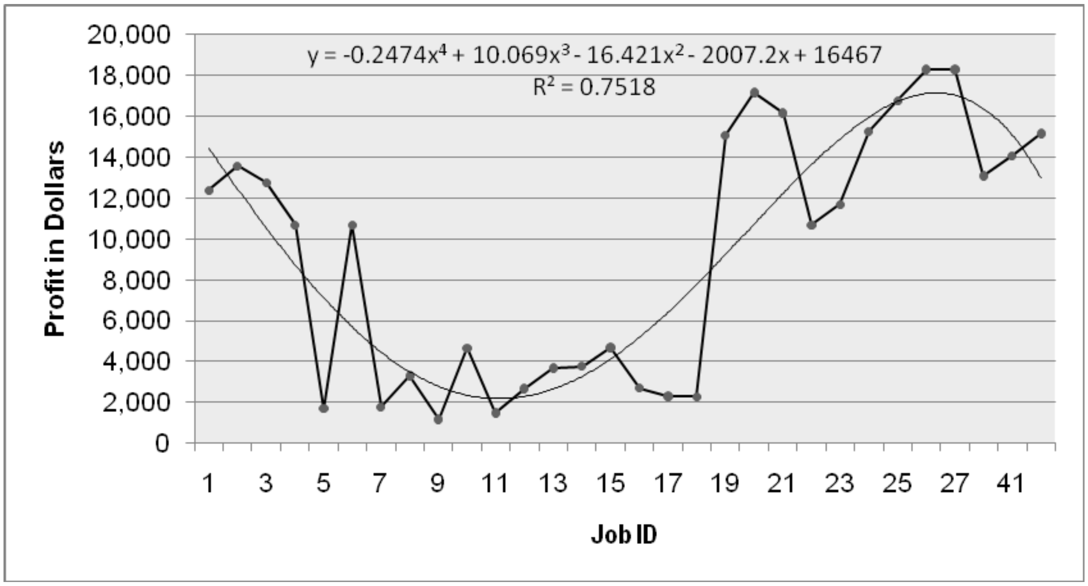


Figure 11 Profit Distribution

Guhya (2010) established a game theory for Reverse Auction game that included an equation for the form of contracts.

$$B_j = \mathrm{K} + \Xi_j\, \Gamma, \tag{3}$$

Γ represents the upper limit the υ player is prepared to pay in the game above the nominal minimum bid amount K. A negative Ξ_j represents a loss on direct costs to the λ_i player who makes this type of bid, and enough of these bids will lead to a bankrupt player. Guhya (2010) also concluded that comparing Ξ can allow a direct comparison with different studied as Ξ is a normalized value of the amount the υ player is willing to accept under the rules of the game. Thus when the data in Figure 12 is normalized and represented in the form of Ξ, the graph can be compared directly with similar graphs of other studies. The issue is that different groups of players will accept a different upper bound to the game. The normalization adjusts all player groups to an equal footing.

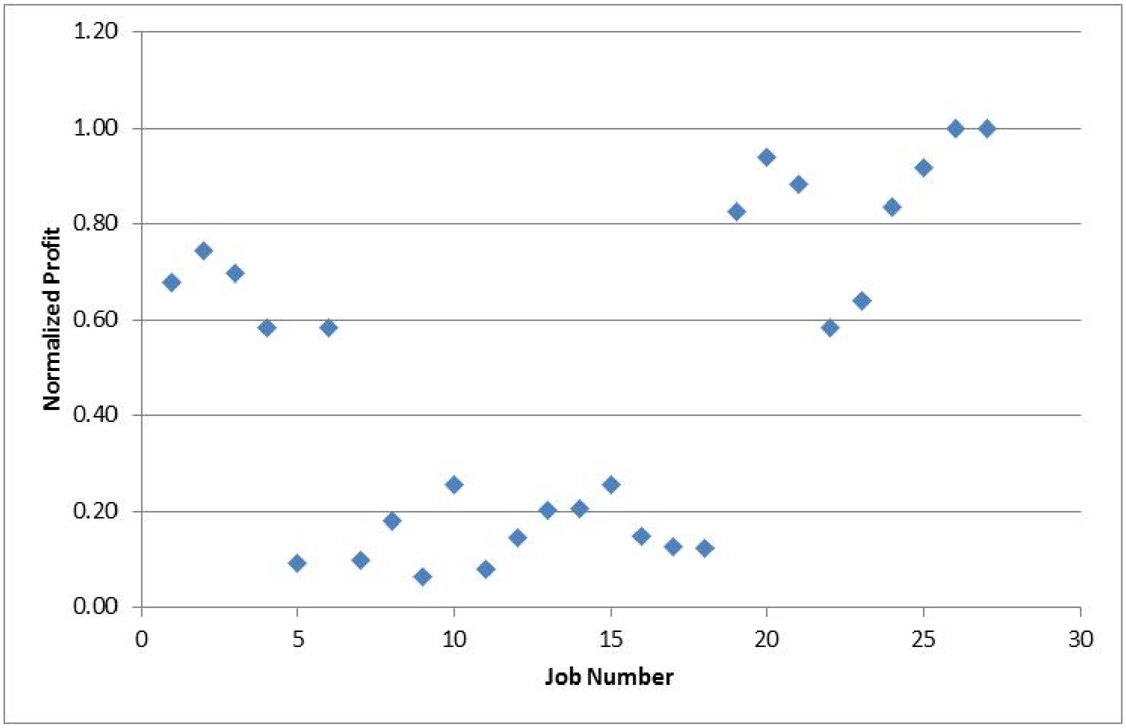


Figure 12 Normalization of Profit Percentages

Values of the normalized date range from just about zero to one. When this range is divided into ten parts of size 0.1, the number of values of Ξ occurring in each part gives the frequency. This assists in directly comparing profit results and reading the data in a different form. Table 5 gives these frequencies.

Table 5 Frequency of Values of Ξ

Ξ Range	Number
Less than 0	0
0 - 0.1	4
0.11 - 0.2	6
0.21 - 0.3	3
0.31 - 0.4	0
0.41 - 0.5	0
0.51 - 0.6	3
0.61 - 0.7	3
0.71 - 0.8	1
0.81 - 0.9	3
0.91 - 1.0	4

Figure 13 plots these values to give a graphical representation.

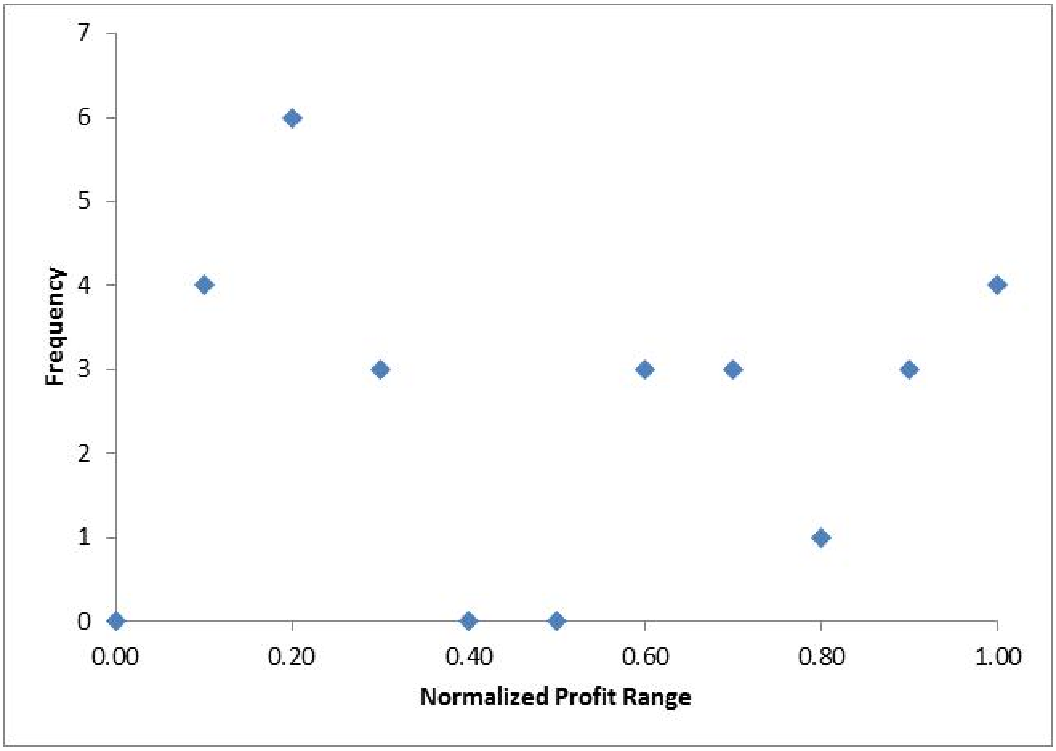


Figure 13 Histogram of Frequency of Ξ

Figure 14 gives each participant's share of winning bids in percentages.

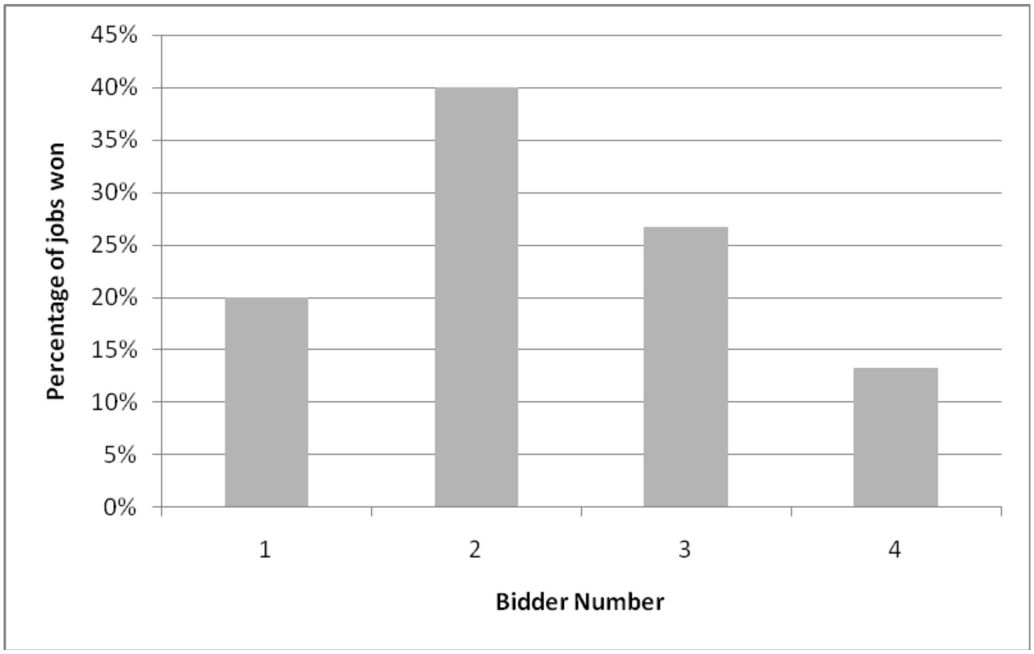


Figure 14 Percentage of Jobs Won by Each Bidder

INCONSISTENCY IN DATA

This study only uses the data recorded in Gujarathi's case study. However there were some inconsistencies observed when conducting this statistical analysis. The Microsoft Access database does not show any bids recorded on job IDs from 28 to 39 as shown in Figure 15. Also the database shows record of bids on job IDs from 43 to 52, there is no data showing the job cost and the profit made on winning bids. Hence these job IDs are not considered under this study.

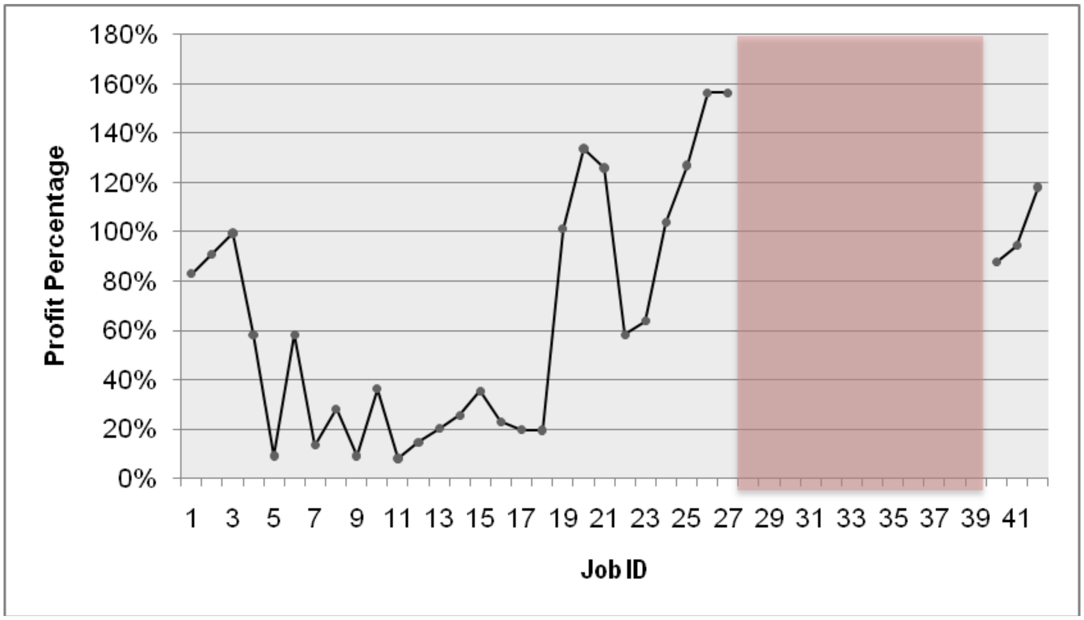


Figure 15 Missing Bid Data

Table 6 shows the bid data summary for each week.

Table 6 Bidding Data

Jobs per Week			
	Total Jobs	Jobs Bid	Job Data Recorded
Week 1	8	8	8
Week 2	10	10	10
Week 3	9	9	9
Week 4	9	9	3
Week 5	9	9	-
Week 6	12	-	-
Week 7	9	-	-
Week 8	11	-	-

CHAPTER IV

RESULTS

INTRODUCTION

The research objectives for this study are similar to study completed by Guhya (2010):

1. Establish plots of the bidding data
2. Compare the bidding patterns shown in the plots with time for all bidders
3. Determine if evidence exists in the bidding data to confirm the existence of the ω game and does it represent some form of collusion
4. Compare the returns of the different bidders in the α game to determine are there are any differences in bidding returns and does it represent some form of collusion

The data from Gujarathi's (2008) case study is comprehensively re-analyzed. The trend periods determined in Gujarathi's data are compared with the trend periods analyzed in van Vleet's data (2004) by Guhya (2010). This comparison enables us to verify the trend periods postulated by Chauhan (2009).

Further results from the descriptive statistics for the bid data provide data to establish plots of the bidding data.

In order to confirm the presence of the ω game and any collusion between players, results from descriptive statistics for the job cost data would be used. These results would also establish plots of bidding data.

For every individual bidder, their bid period statistics are studied to give bidding history and graphically represent it. Later the bid data is converted to statistics with respect to the dollar difference in the winning and next higher bid. This differential bid statistics provide basis to investigate tacit collusion amongst bidders.

COMPARING BIDDING TRENDS

Chauhan (2009) postulated that all Reverse Auction Bidding systems show distinct set of four different periods. The job profit data from van Vleet's case study analyzed by Guhya (2010) is given in Figure 16.

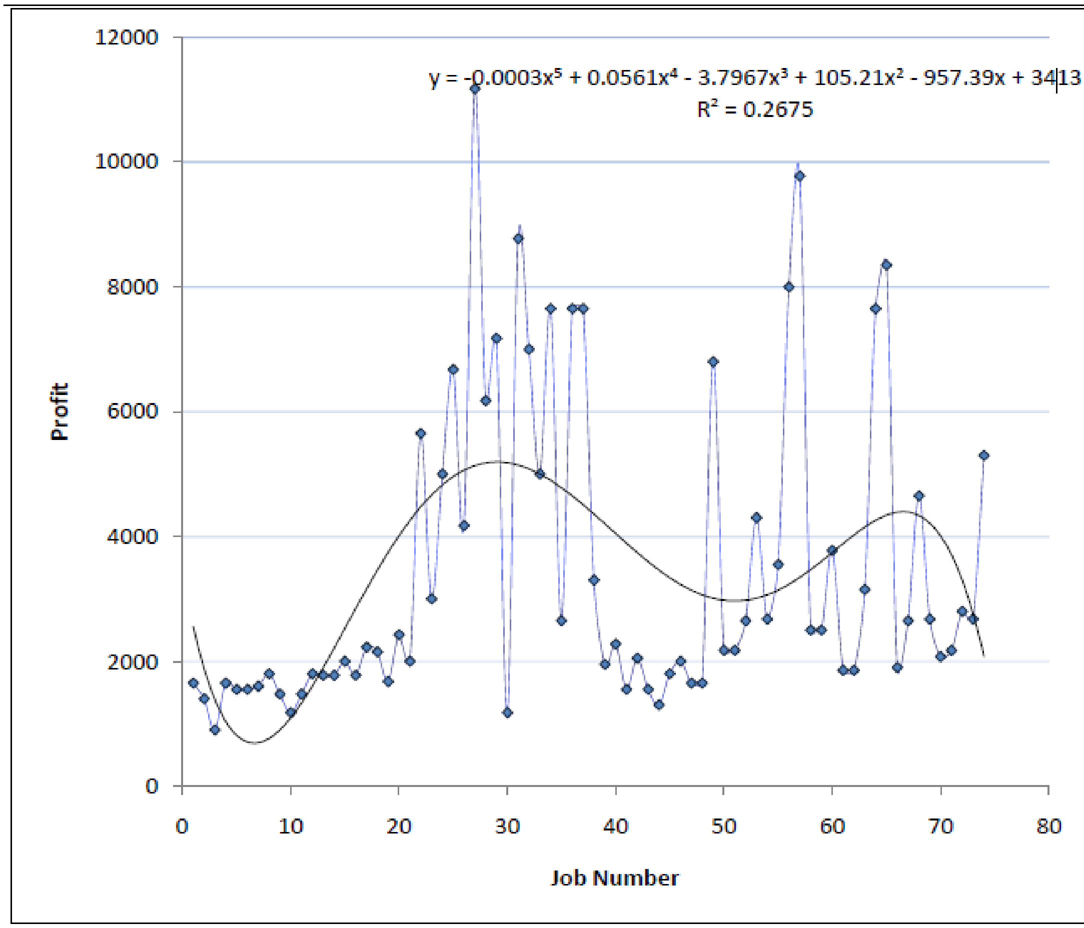


Figure 16 Job Profit Data from van Vleet (Guhya 2010)

Guhya establishes the same bidding trends given in Table 7.

Table 7 Trend Periods in van Vleet's Data

Job ID	Trend Characteristic
1 to 20	Learning
21 to 40	Discovering
41 to 51	Competitive
52 to76	Profit

The data from Gujarathi's case study showed an interesting pattern similar to the four trend periods postulated by Chauhan (2009). These bidding patterns are said to be observed in a typical Reverse Auction system. It is observed from Figure 17 that the bidders started the game with high bids. Then as the competition grew, their bid amounts dropped. As the game progressed the bidders developed proficiency and maximized their profits towards the end. The bid amounts range from \$14,000 to \$30,000.

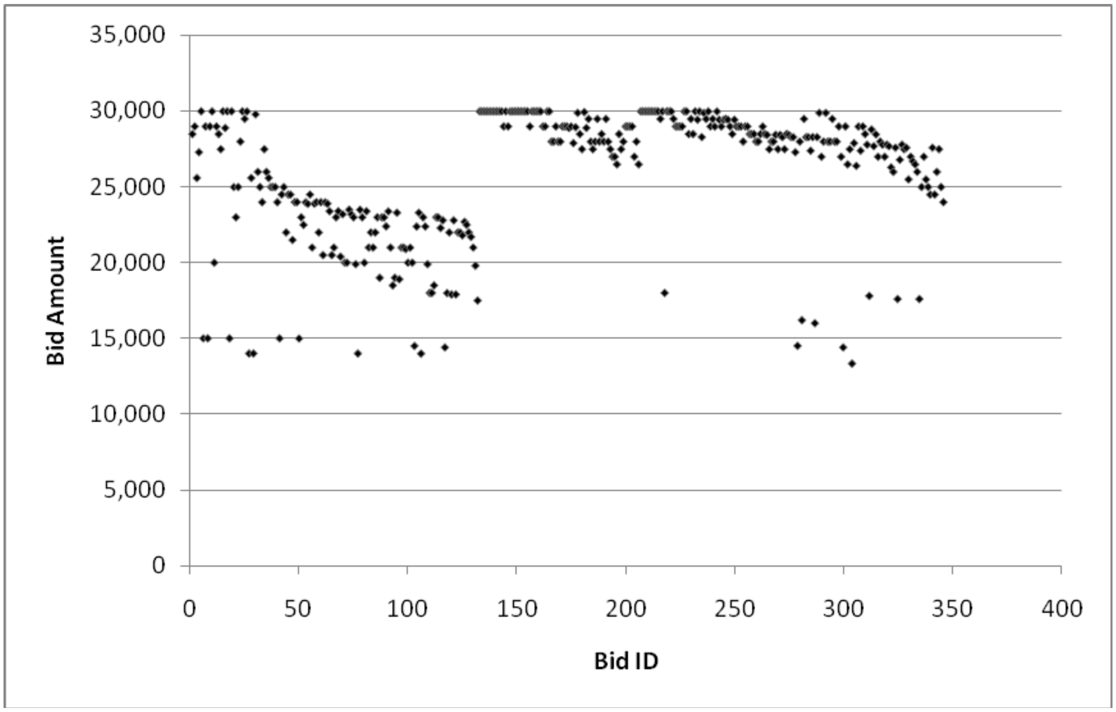


Figure 17 Bid Distribution

It is considered from Figure 18 that the competition amongst the bidders caused the winning bids to drop considerably to $14,000 from Job Number 9 to 18, as is usual in Reverse Auction game play. Then the bidders seem to have developed a game play understanding and started winning the jobs at a much higher price and won most of the later jobs (from 19 to 42) at a consistently higher bid amount. This graph strongly suggests the tacit collusion exists amongst the bidders. However what caused the sudden rise in prices or what behavior of the bidders caused it is not clear from the results.

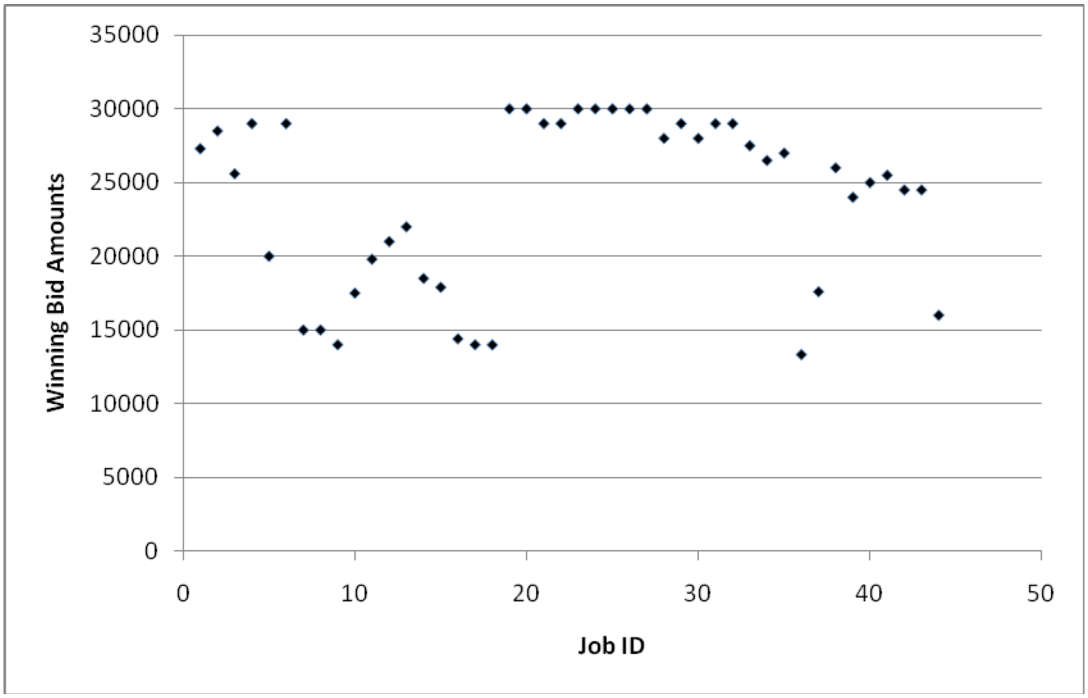


Figure 18 Distribution of Winning Bids

In order to observe the bidding trends in the data, the data in Figure 18 had to be converted from bidding amounts to the profit percentages to accurately identify the trends postulated by Chauhan (2009) as seen in Figure 19.

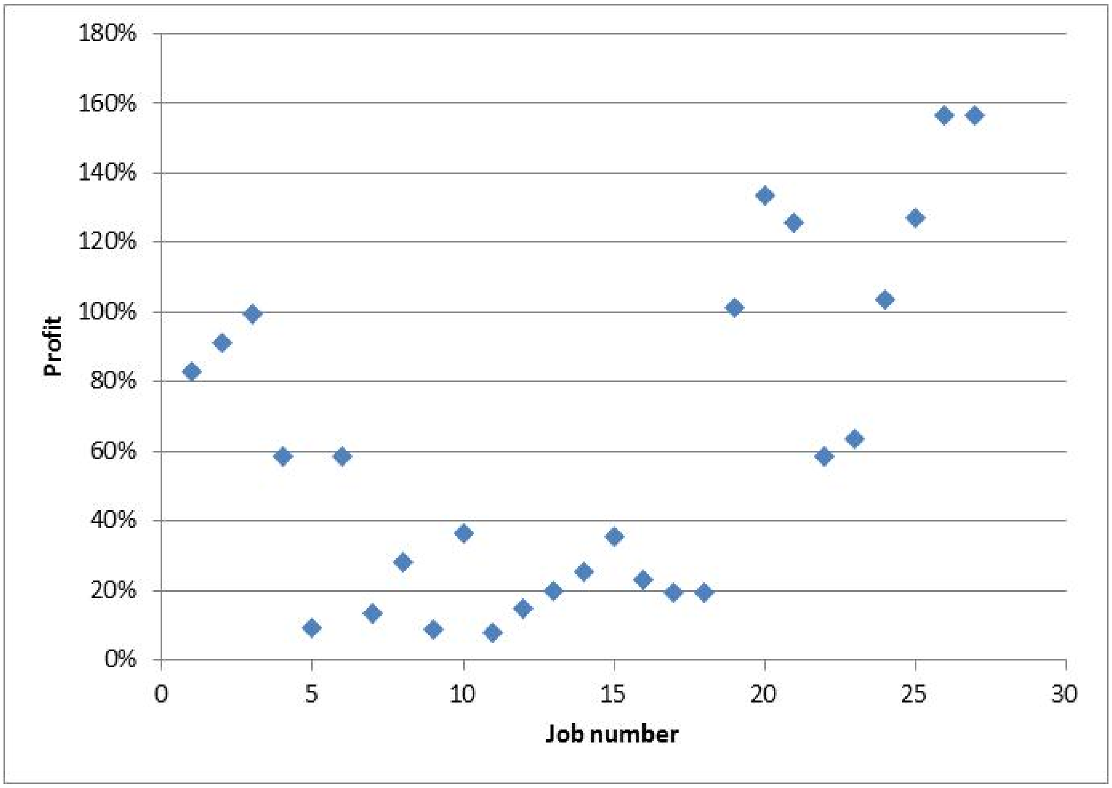


Figure 19 Job Profit Data Relative to Costs

Figure 20 shows a linear trend line fitted to the data in Figure 19. The positive slope of the line shows an increase in the profit percentages. However the scattered nature of the plot does not make the trend a good fit. This is also clear from the statistical value of $R^2 = 0.23$.

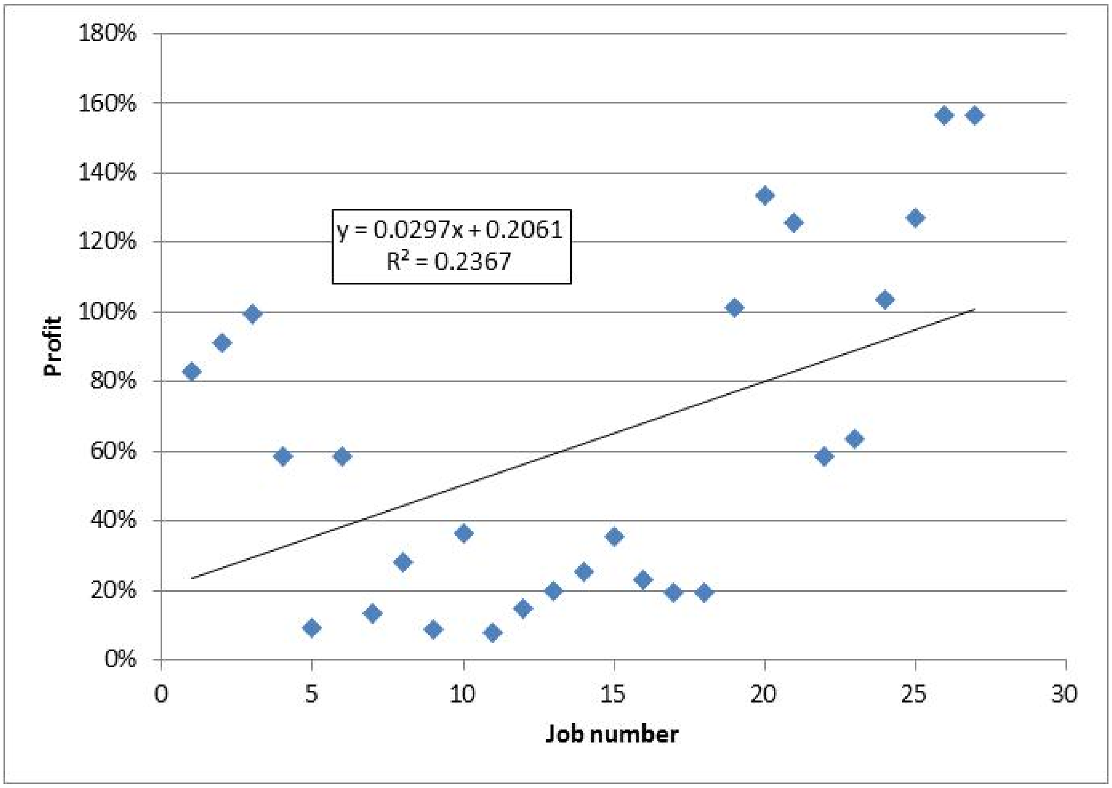


Figure 20 Job Profit Data Relative to Costs with Addition of Trend Line

Due to the imprecise fit of the linear trend line, Rogers (2010) suggested that a fifth order polynomial trend line be fitted to the data to reveal a better nature of the plot as shown in Figure 21.

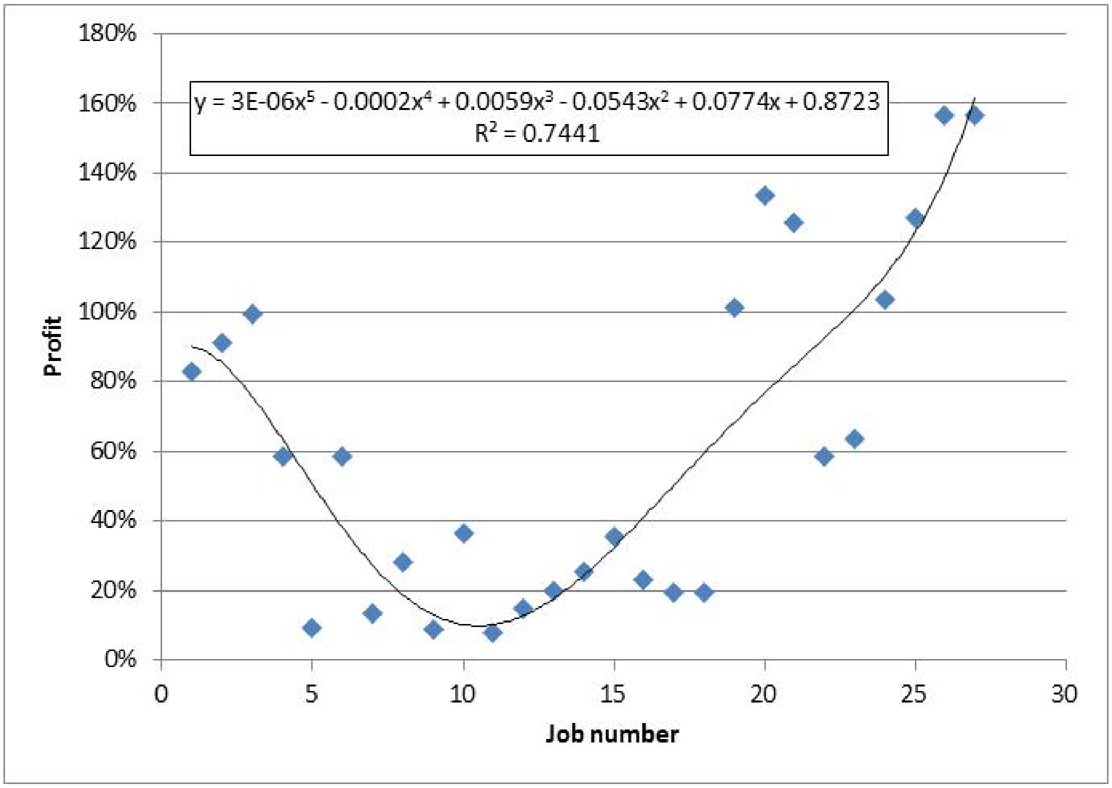


Figure 21 Job Profit Data Relative to Costs with Polynomial Trend Line

We observe that the R^2 value has significantly gone up to 0.74. Although not very accurate, the trend line reveals the changes in the bidding patterns. According to Nichols (2010), these patterns are typically observed if all participants have no prior experience in Reverse Auctions.

Figure 22 identifies the bidding trends that are postulated by Chauhan (2009). The bidders start with higher bids, then as the competition rises, their profits drop until λ_i player discovers that the competition has lowered their profits and then starts winning jobs at a higher profit. The other players learn quickly and that is followed by a long period of high profits.

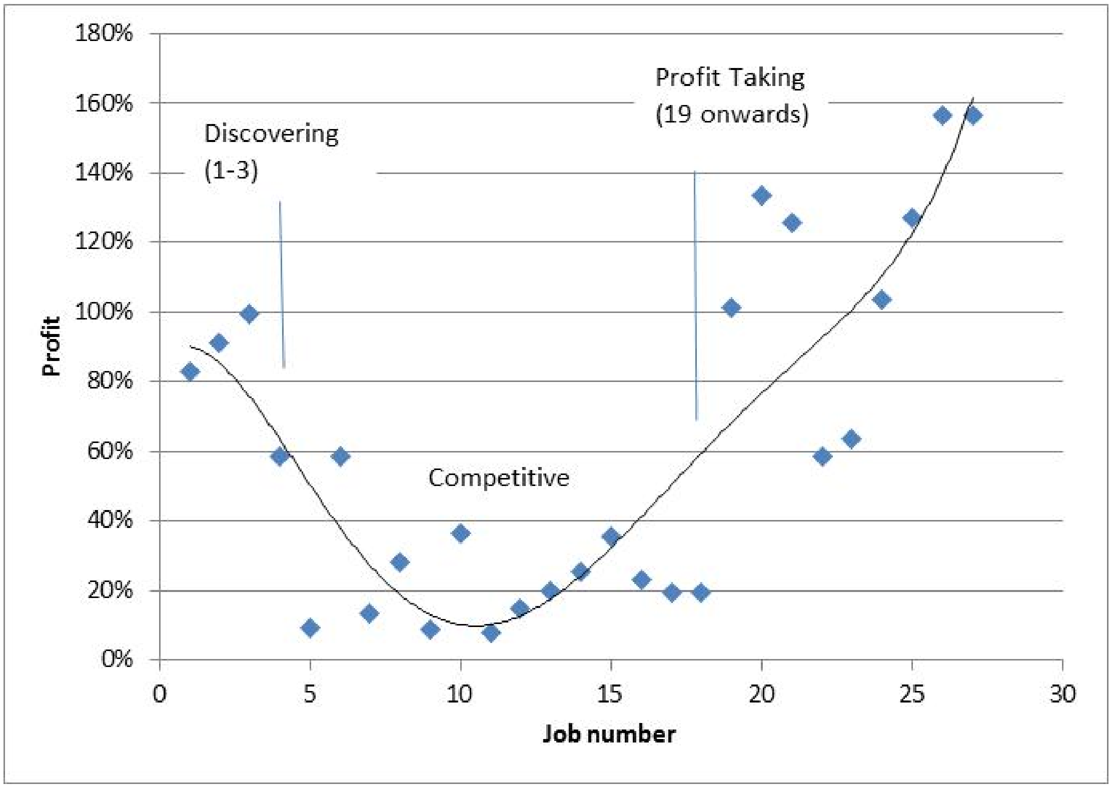


Figure 22 Identifying the Bidding Trends in Gujarathi's Data

These periods are summarized in Table 8.

Table 8 Chauhan's Postulated Bidding Trend Periods

Job ID	Trend Characteristic	Comment
0 to 6	Discovering	Characterized by small bursts of profits
7 to 18	Competitive	All players repetitively making low profits
19 to 42	Profit	Overall high profits by all bidders

It can be confirmed that the trend periods are significantly distinct from each other by performing a Student's t-Test. The values from the three periods can be cross tested by forming six pairs of data. Thus Table 9 shows three values across and confirms that each data pair comes from a different data set having different statistical characteristics.

Table 9 Comparison of Data Using Student's T-Test

Stage	1	2	3
1	-	2.44	4.35
2		-	9.88

On comparing the Gujarathi's data to van Vleet's data based on job profit data, the trend periods do show some resemblance. However they also show significant differences. The first striking difference is in the learning phase. Guhya's analysis shows that the learning phase is characterized by constant lower amount bids, whereas in Gujarathi's data, the learning phase is absent as the bidders start the game with high amount bids. This could be due to the difference in the number of bidders in the two case studies, the personality types of the bidders or different learning curves of the participating bidders. The other key distinction is in the final trend of profit gain. The comparison between the two data sets is summarized in Table 10.

Table 10 Comparison of Trend Periods

Trend Characteristic	Van Vleet	Gujarathi
Learning	Extended period, relatively lower profits	Not observed
Discovering	Profits rising	Short but similar
Competitive	Consistent low profits	Very similar
Profit Gain	Long period, high profits	Similar

DESCRIPTIVE STATISTICS OF THE BID DATA

Every bidder plays the Reverse Auction Bidding game with his unique set of strategies. In order to look further into this, bid data needs to be studied with respect to the frequency of bids per job per week given by Table 11.

Table 11 Frequency of Bids per Job per Week

Week	Jobs	Bids
1	8	13
2	10	119
3	9	16
4	9	58
5	9	140
6	-	-
7	-	-
8	-	-
Total	45	346

The bid data shows considerable variation in the rate of bidding. This is also due to the data missing for Job IDs 28 to 39. Next step would be to compare the number of bids placed by each bidder to the number of jobs won. This is given in Table 12.

Table 12 Comparing Number of Bids to Number of Jobs Won by Bidders

Rank	Participant	Bids Placed	Jobs Won
1	3	77	8
2	2	101	12
3	1	88	6
4	4	80	4
	Total	346	30

Clearly some bidders are more efficient at bidding than the other. It is clear that there is no direct relationship between the number of bids placed to jobs won. This makes it clear that the high ranking bidder used some strategy to outbid the lower ranking bidders. This is an area of future research.

Also, bidder ranking 2, won more jobs than bidder ranking 1. So bidder 1's average profit per job must be higher than that of bidder 2. Table 13 summarizes the profit data for every bidder.

Table 13 Profit Data for Each Bidder

Rank	Participant	Loan ($)	Profit ($)
1	3	11500	84257
2	2	12500	76205
3	1	4500	69987
4	4	4000	47629

Here, the relationship between the loan amount and profit made shows that the higher the loan amount used in the game typically results in a higher profit in the game. The relationship is not exact, but it has been found in other case studies. This can be illustrated by plotting the two variables in Figure 23.

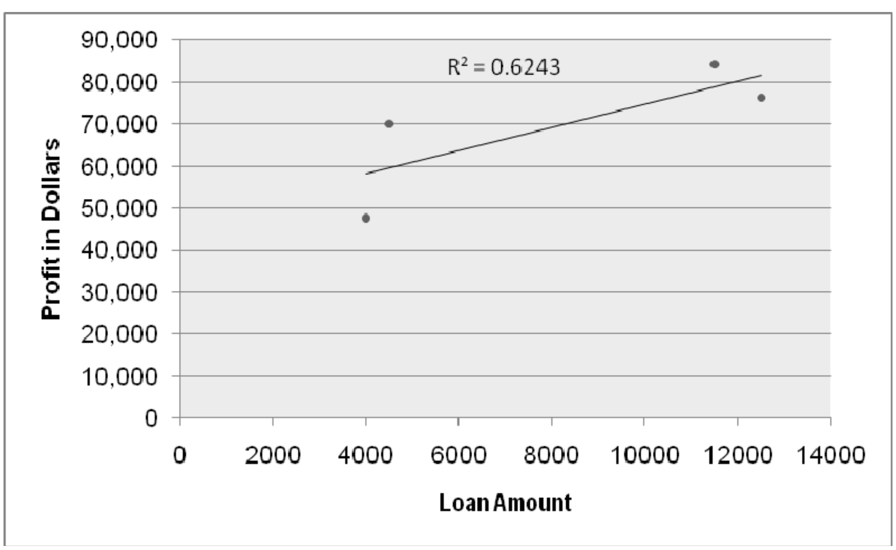


Figure 23 Comparing the Loan Amount to the Profit Made

According to Nichols (2010), bid efficiency of bidders may be a gauge of their success. Table 14 shows the bid efficiency data.

Table 14 Bid Efficiency of Bidders

Rank	Bidder	Bids Placed	Jobs Won	Bid Efficiency (%)
1	3	77	8	10.39
2	2	101	12	11.88
3	1	88	6	6.82
4	4	80	4	5.00
	Total	346	30	8.67

DESCRIPTIVE STATISTICS OF THE WINNING JOB DATA

Table 15 shows the profit efficiency of all bidders.

Table 15 Profit Efficiency of Bidders

Rank	Bidder	Profit ($)	Profit Efficiency ($)
1	3	84257	10532.13
2	2	76205	6350.42
3	1	69987	11664.50
4	4	47629	11907.25
TOTAL		278078	9269.27

Ironically the bidder having lowest ranking and lowest number of bids has the highest profit efficiency followed by the next low ranking bidder. The conclusion is that seeking higher profit may not yield the greatest number of jobs or the highest overall returns.

Table 16 shows the profit efficiency of the bidders in van Vleet's data and here too there does not seem to be any relation between the profit efficiency and profit rankings of the bidders.

Table 16 Profit Efficiency of Bidders from van Vleet's Data

Rank	Bidder	Profit ($)	Profit Efficiency ($)
1	5	91673	5392.50
2	3	59170	2689.50
3	4	53025	4078.00
4	1	37559	2347.00
5	2	24650	3081.25

Figure 24 shows the number of jobs won by each bidder.

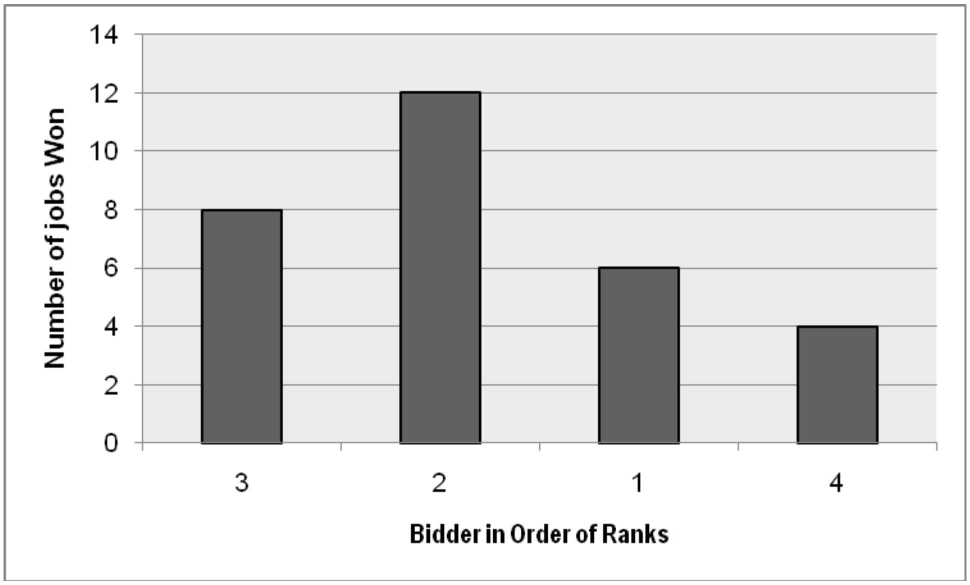


Figure 24 Jobs Won by Bidders

The next stage would be to study the profit percentages of individual bidders. This data would give insight whether any pattern or relationship exists in the data. Figures 25 to 28 plot profit percentages of individual bidders with respect to the jobs won. Figure 29 shows the profit percentages for all bidders in the game.

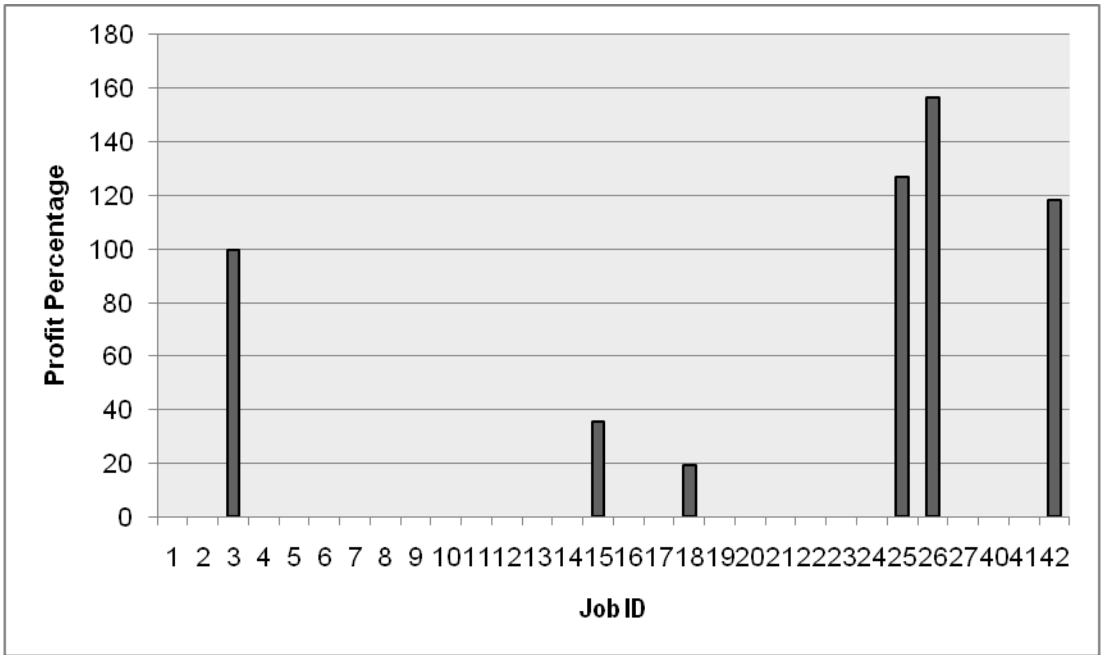


Figure 25 Profit Percentages - Bidder 1

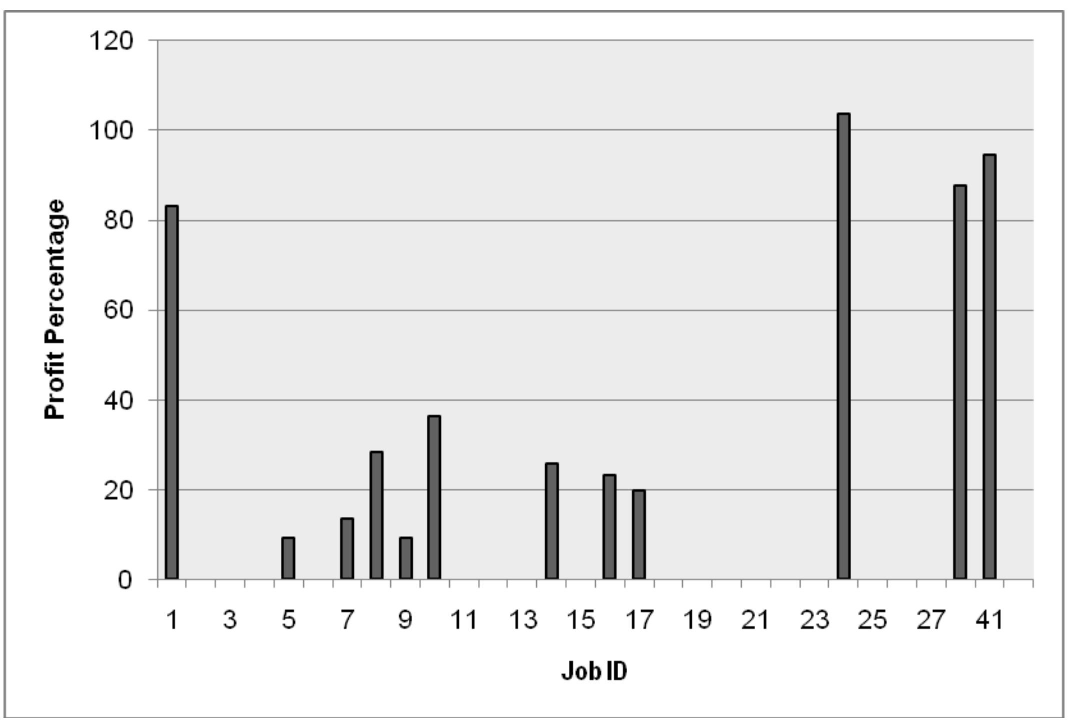


Figure 26 Profit Percentages - Bidder 2

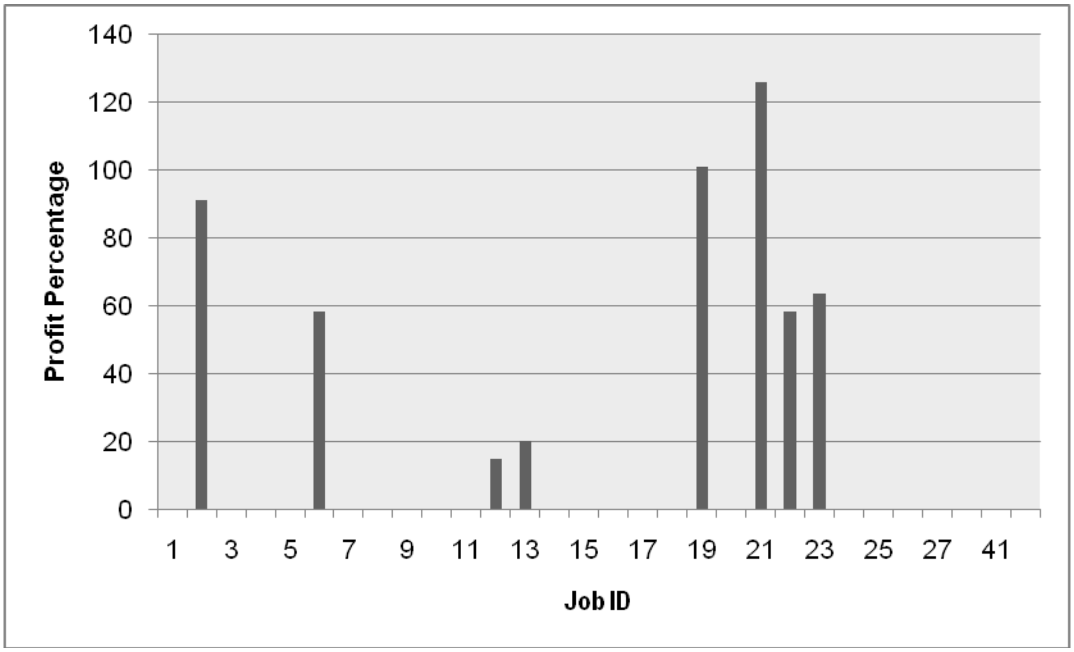


Figure 27 Profit Percentages - Bidder 3

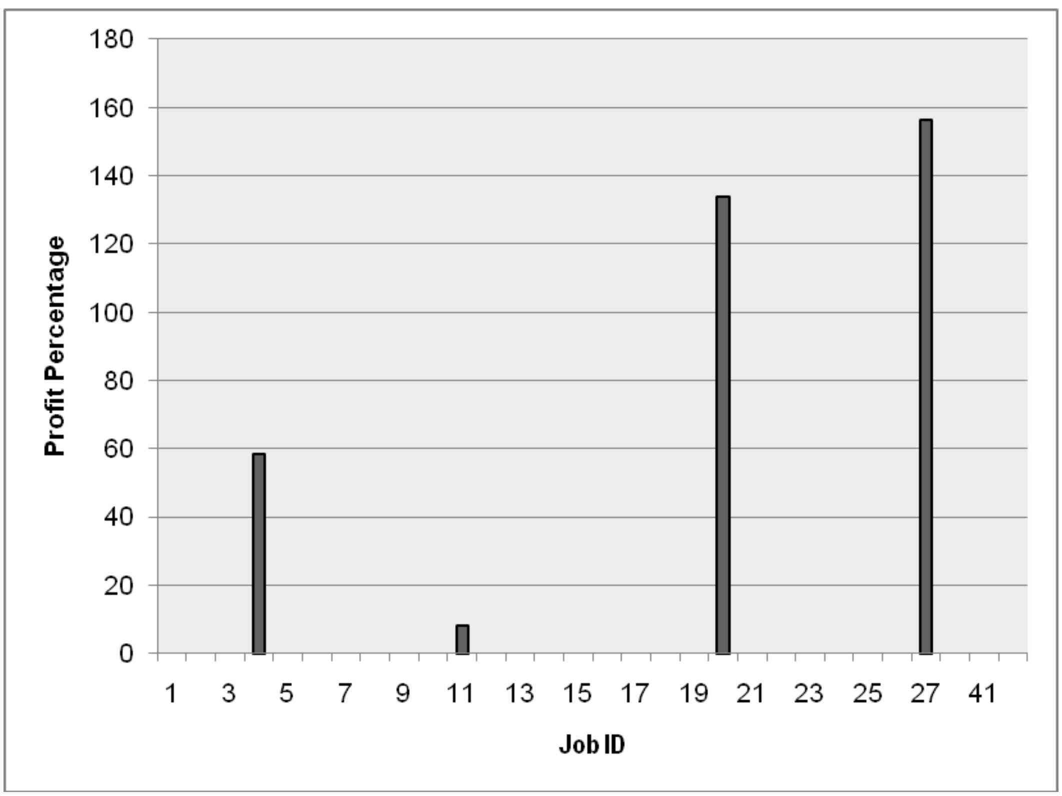


Figure 28 Profit Percentages - Bidder 4

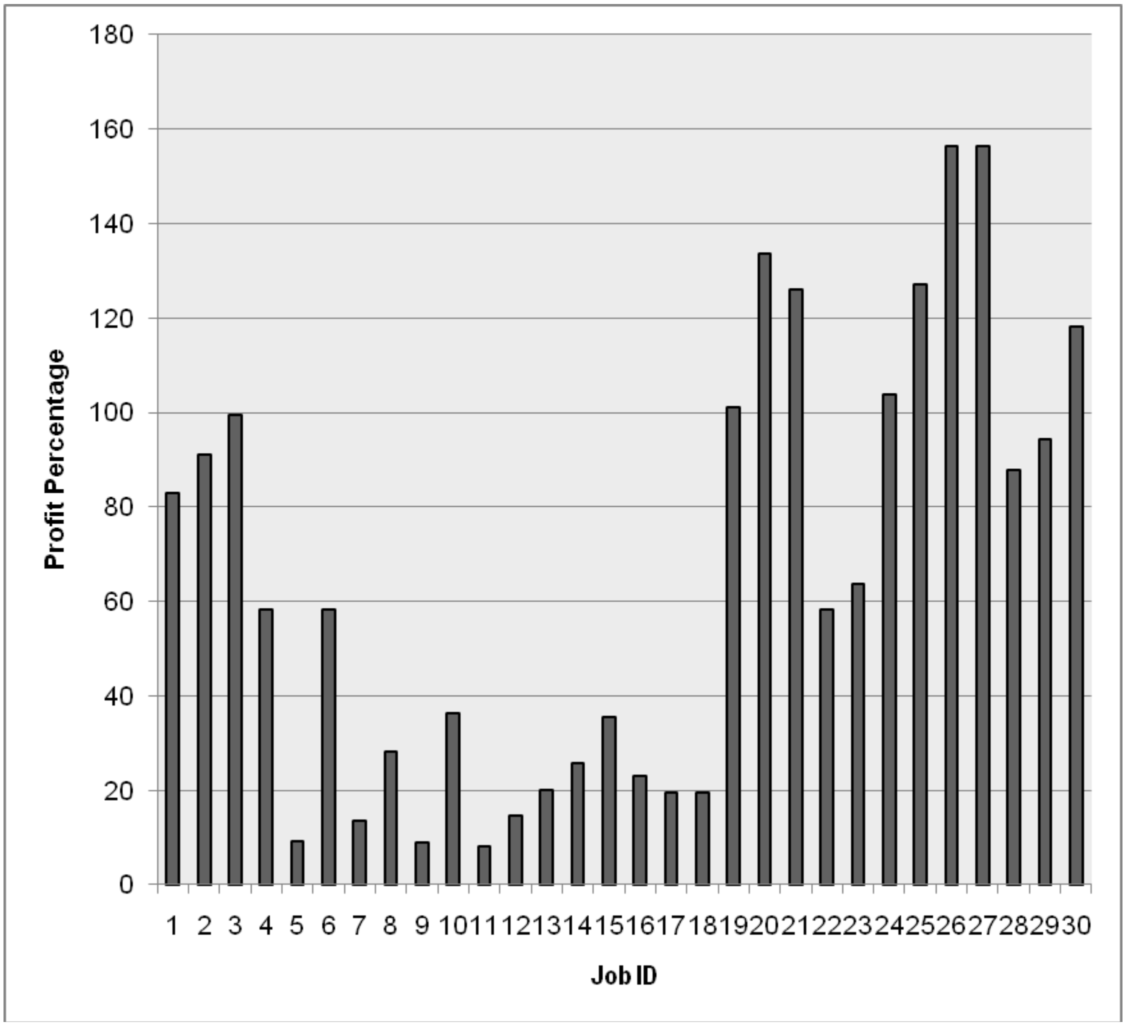


Figure 29 Profit Percentages - All Bidders

Figures 30 to 33 show the frequency of each bidder winning in each profit percentage range and Figure 34 combines the frequency of all bidders.

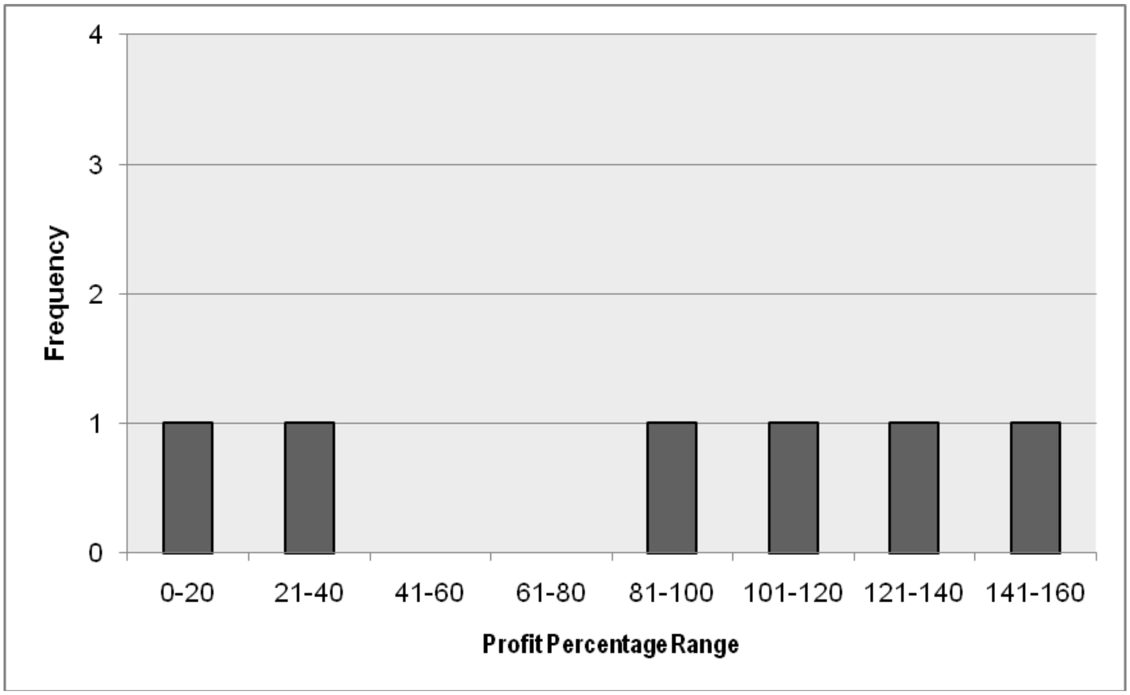


Figure 30 Frequency of Winning Bids in Profit Percentage - Bidder 1

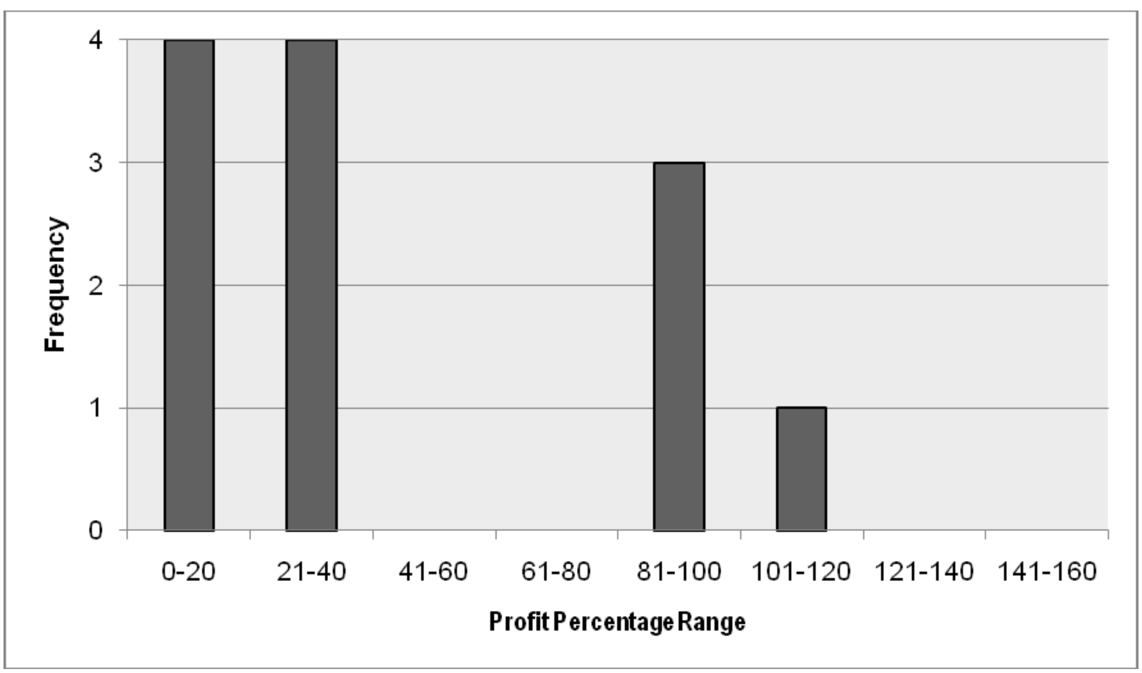


Figure 31 Frequency of Winning Bids in Profit Percentage - Bidder 2

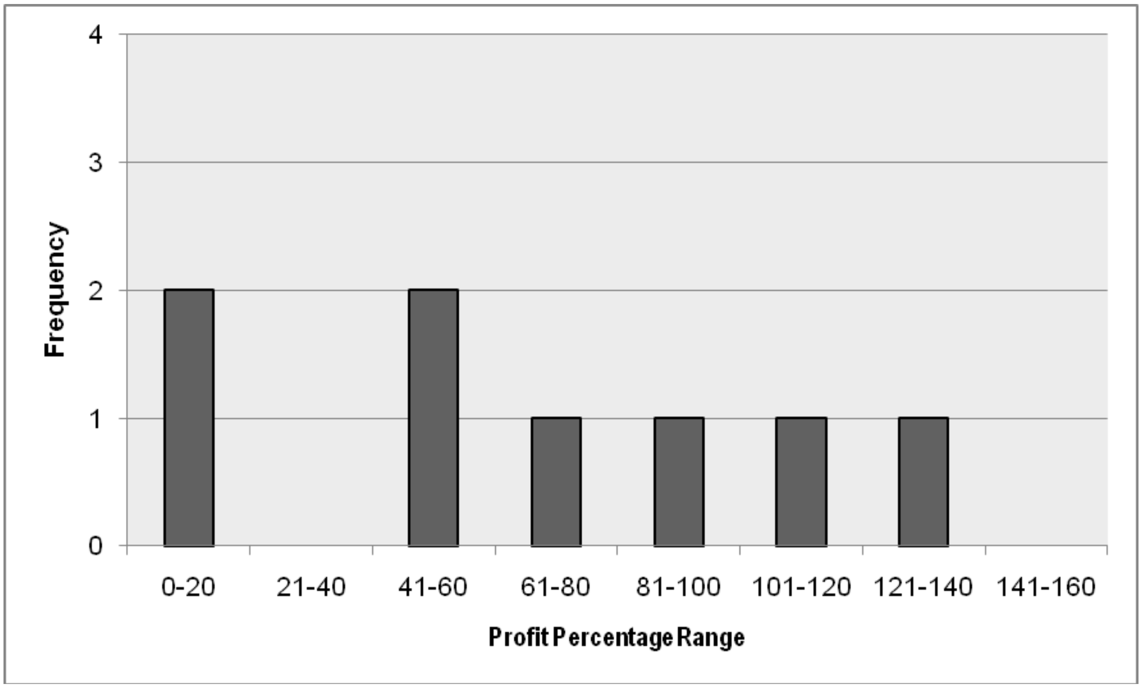


Figure 32 Frequency of Winning Bids in Profit Percentage - Bidder 3

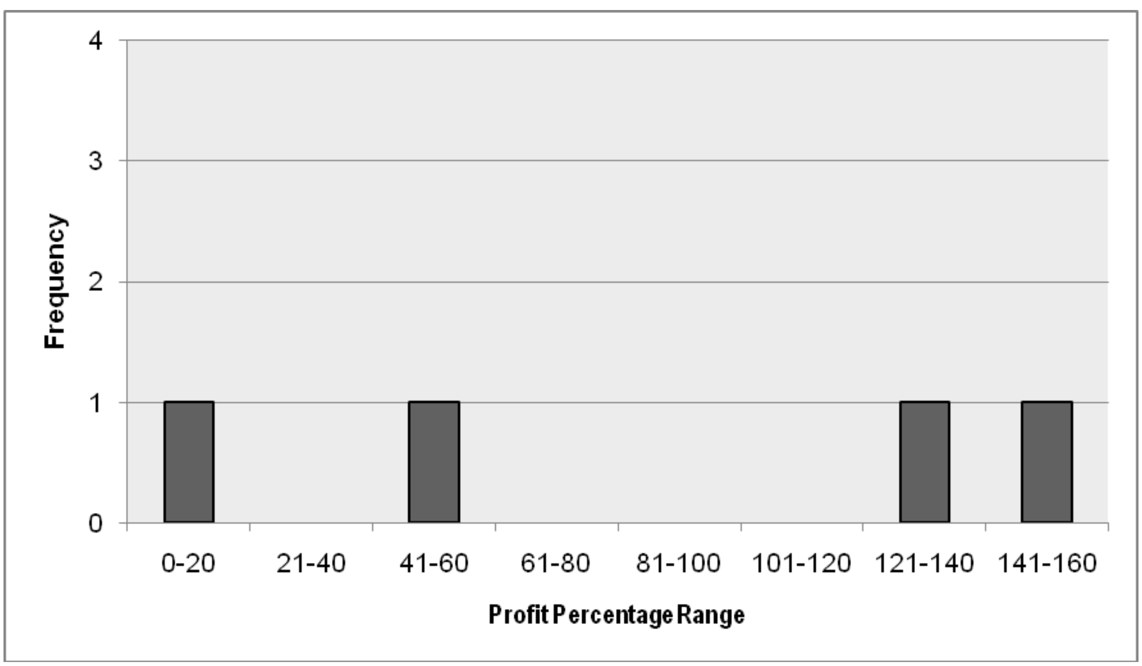


Figure 33 Frequency of Winning Bids in Profit Percentage - Bidder 4

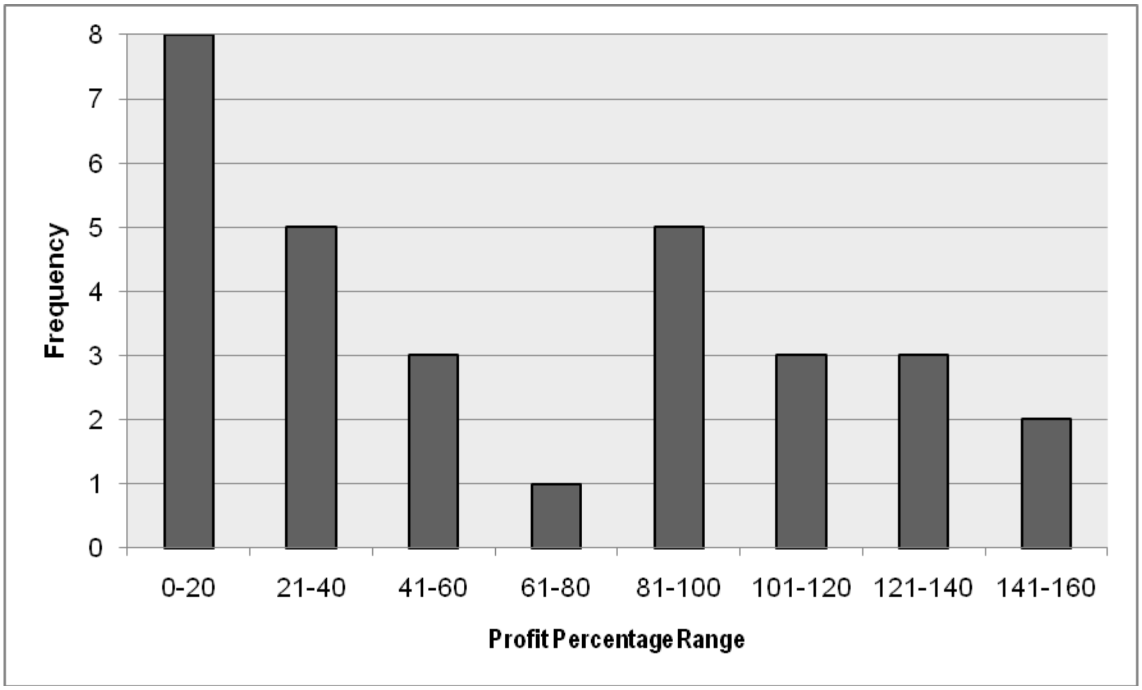


Figure 34 Frequency of Winning Bids in Profit Percentage - All Bidders

BID PERIOD COMPARISON

Tables 17 to 21 outline the bidding behavior with respect to time. It is observable that every bidder has a different bidding strategy and they all get aggressive towards the end of every bidding week.

Table 17 Bids Made per Minute - Bidder 1

	4:00-4:15	4:20-4:35	4:40-4:55	5:00-5:15	5:20-5:35	5:40-5:55	Total Bids
1	0	2	0		0	0	2
2	0	2	0		0	1	3
3	0	2	0		0	0	2
4	0	4	0		0	1	5
5	3	0	0		0	0	3
6	1	3	0		0	0	4
7	0	1	3		2	0	6
8	0	6	1		1	3	11
9	0	6			0	4	10
10	0	1			0	0	1
11	0	2			2	4	8
12	0	3			1	5	9
13	0	2			2	5	9
14	0	7			1	7	15

Table 18 Bids Made per Minute - Bidder 2

	4:00-4:15	4:20-4:35	4:40-4:55	5:00-5:15	5:20-5:35	5:40-5:55	Total Bids
1	0	0	0		3	5	8
2	0	3	0		2	0	5
3	0	3	0		2	1	6
4	0	1	0		0	1	2
5	1	2	0		3	1	7
6	0	0	0		0	2	2
7	0	1	1		0	3	5
8	1	1	1		0	2	5
9	0	2			2	9	13
10	1	0			0	4	5
11	1	2			0	5	8
12	0	2			4	5	11
13	0	2			1	4	7
14	0	2			5	9	16

Table 19 Bids Made per Minute - Bidder 3

	4:00-4:15	4:20-4:35	4:40-4:55	5:00-5:15	5:20-5:35	5:40-5:55	Total Bids
1	0	0	0		2	0	2
2	0	2	0		3	0	5
3	0	1	0		1	2	4
4	0	3	0		0	1	4
5	0	0	0		0	2	2
6	0	1	1		0	0	2
7	0	1	3		0	1	5
8	0	2	2		0	0	4
9	0	2			2	0	4
10	2	0			2	3	7
11	1	3			0	3	7
12	0	3			1	4	8
13	0	2			0	4	6
14	1	5			4	7	17

Table 20 Bids Made per Minute - Bidder 4

	4:00-4:15	4:20-4:35	4:40-4:55	5:00-5:15	5:20-5:35	5:40-5:55	Total Bids
1	0	2	0		2	0	4
2	0	0	0		2	2	4
3	0	4	0		0	1	5
4	0	5	0		2	1	8
5	0	0	0		1	2	3
6	0	0	0		0	0	0
7	0	2	3		0	5	10
8	0	3	1		2	4	10
9	0	6			0	3	9
10	0	1			0	4	5
11	0	0			0	2	2
12	0	1			1	0	2
13	0	3			1	4	8
14	1	5			1	3	10

Table 21 Bids Made per Minute - All Bidders

	4:00- 4:15	4:20- 4:35	4:40- 4:55	5:00- 5:15	5:20- 5:35	5:40- 5:55	Total Bids
1	0	4	0		7	5	16
2	0	7	0		7	3	17
3	0	10	0		3	4	17
4	0	13	0		2	4	19
5	4	2	0		4	5	15
6	1	4	1		0	2	8
7	0	5	10		2	9	26
8	1	12	5		3	9	30
9	0	16			4	16	36
10	3	2			2	11	18
11	2	7			2	14	25
12	0	9			7	14	30
13	0	9			4	17	30
14	2	19			11	26	58

The data in tables 17 to 21 when plotted in a histogram form, the late bidding phenomena is evident in the results. This is entirely consistent with the findings of Guhya, Figures 35 to 39 shows the plots.

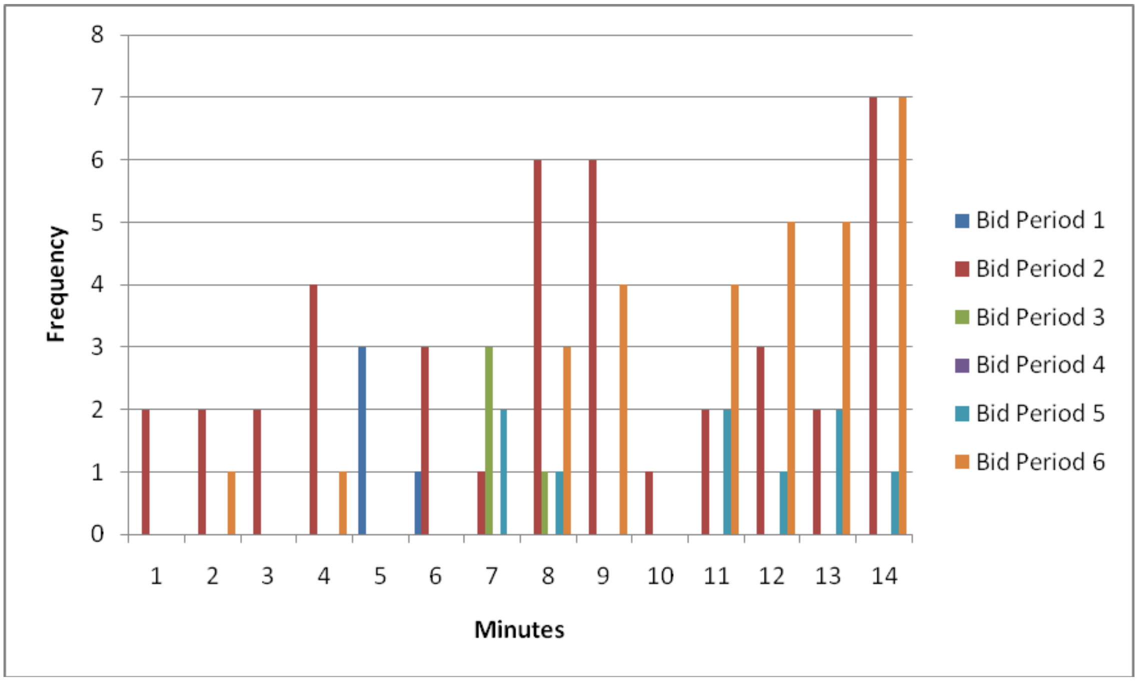


Figure 35 Bid Distribution per Minute - Bidder 1

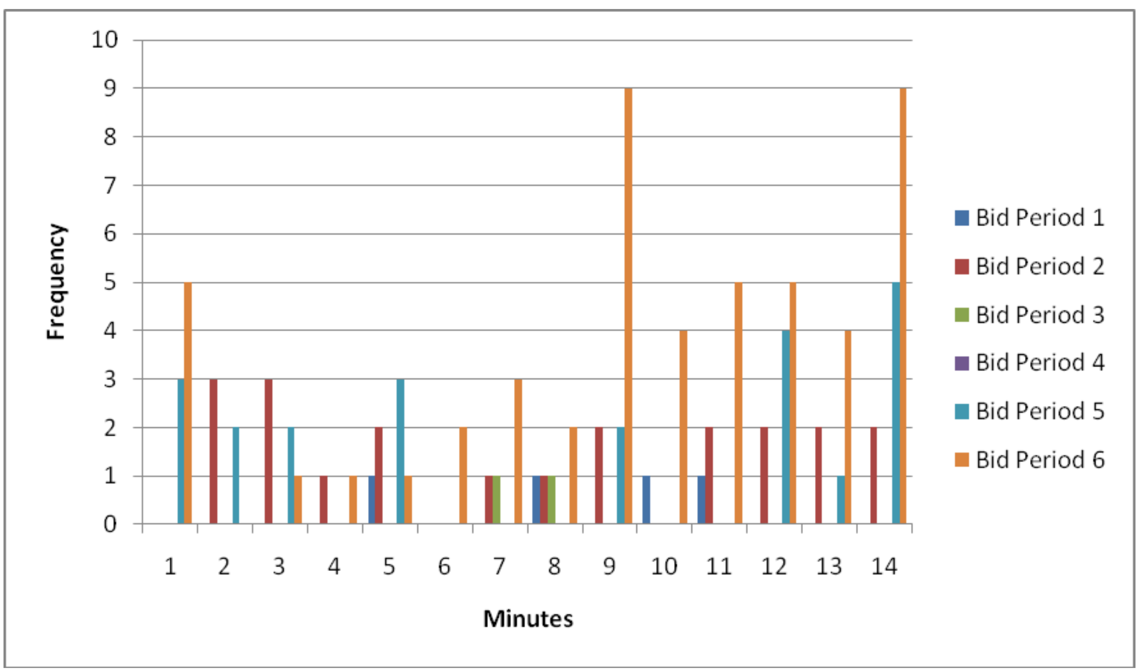


Figure 36 Bid Distribution per Minute - Bidder 2

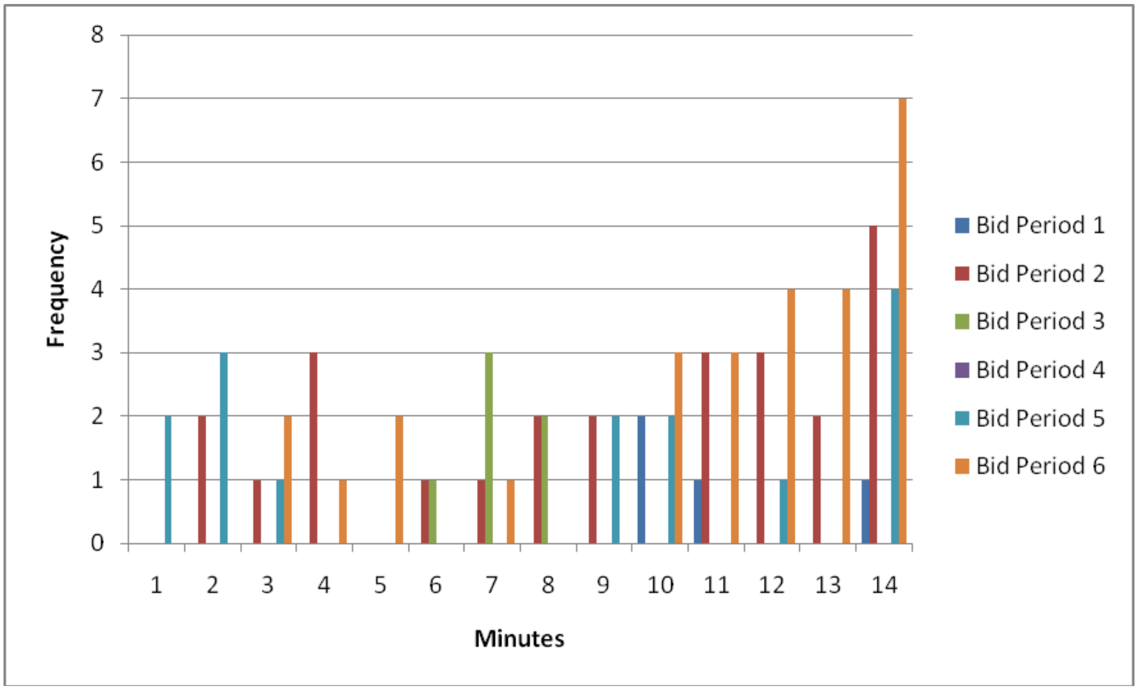


Figure 37 Bid Distribution per Minute - Bidder 3

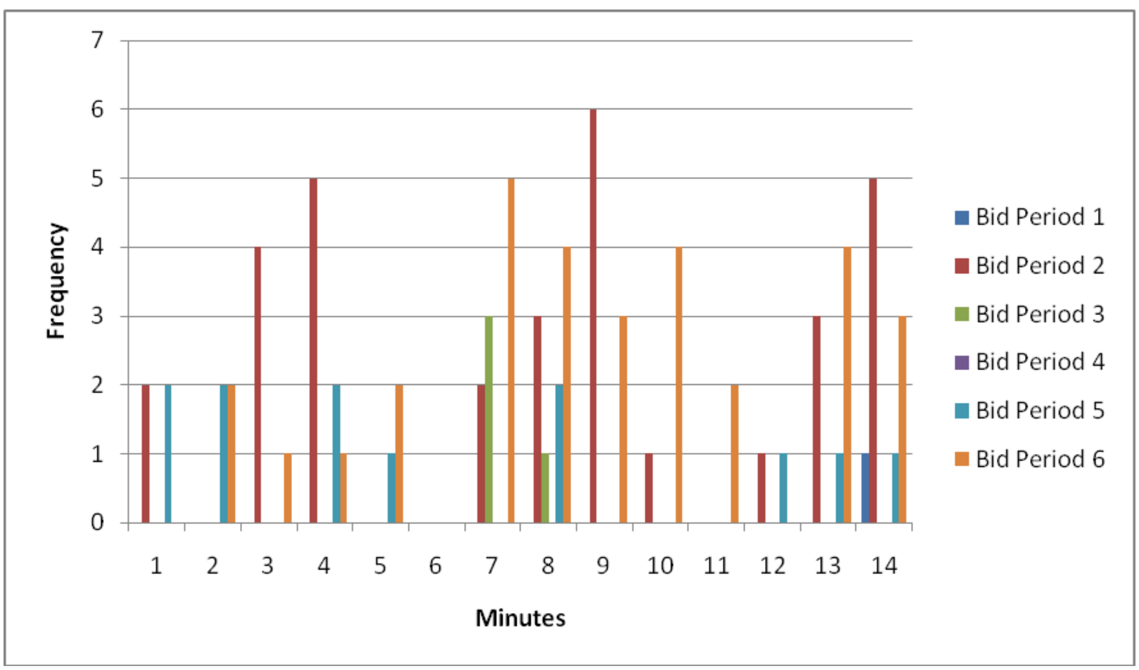


Figure 38 Bid Distribution per Minute - Bidder 4

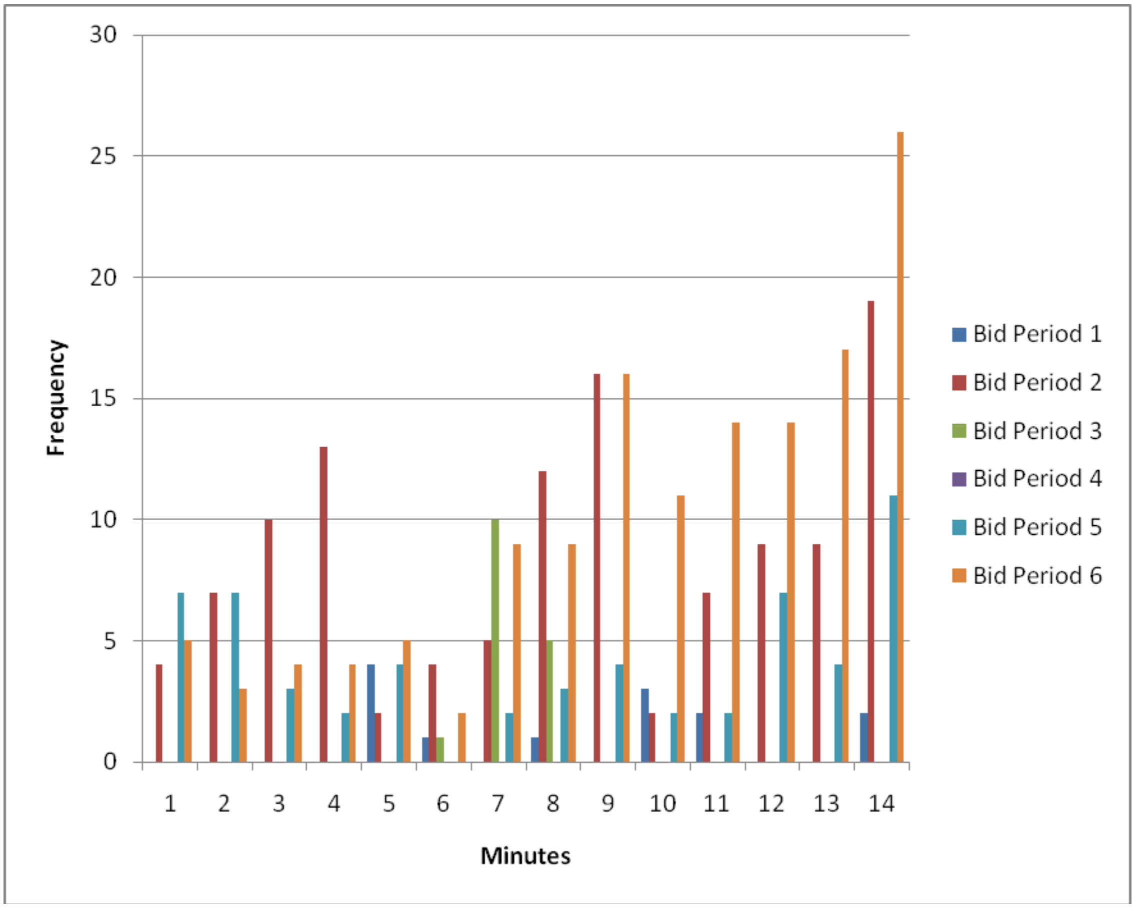


Figure 39 Bid Distribution per Minute - All Bidders

The plots show that overall the bidders start slow and big aggressively in the last five minutes, except for Bidder 4 whose bidding rate was somewhat constant over the bidding period. However this bidder achieved the lowest return on investment.

Bidder 3 with the highest economic gain always bid aggressive in the last three minutes, whereas Bidder 2 with highest number of winning bids bid aggressive at the start, around minute nine and again in the last two minutes.

Table 22 shows the high, low and average bids per minute during the duration of the game.

Table 22 Highest, Lowest and Average Bids per Minute

Minutes	1	2	3	4	5	6	7	8	9	10	11	12	13	14
High	7	7	10	13	4	4	10	12	16	11	14	14	17	26
Low	0	0	0	0	0	0	0	1	0	2	2	0	0	2
Average	3.5	3.5	5	6.5	2	2	5	6.5	8	6.5	8	7	8.5	14

These values are plotted in Figure 40.

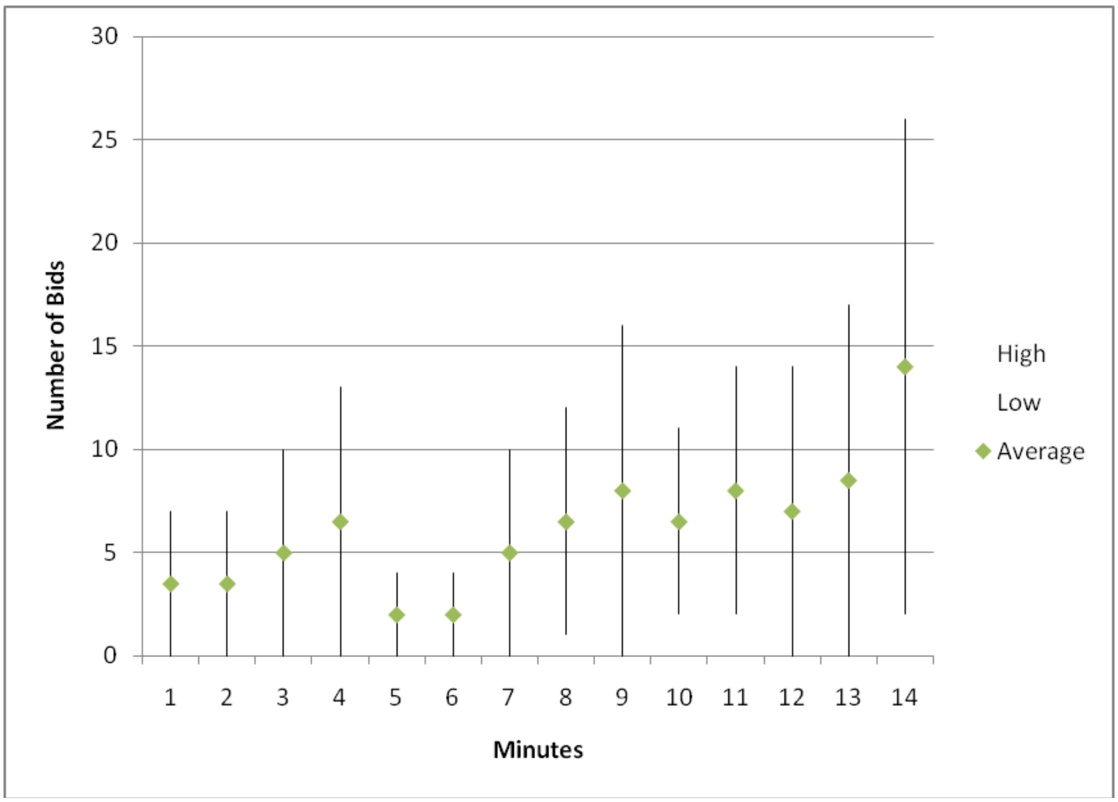


Figure 40 Highest, Lowest and Average Bids per Minute

The average bids per minute show a graduate increase in number of bids and grows high in the last two minutes of the game. The rise in average bids around minute four and nine can be attributed to the players who were constantly aggressive throughout the game.

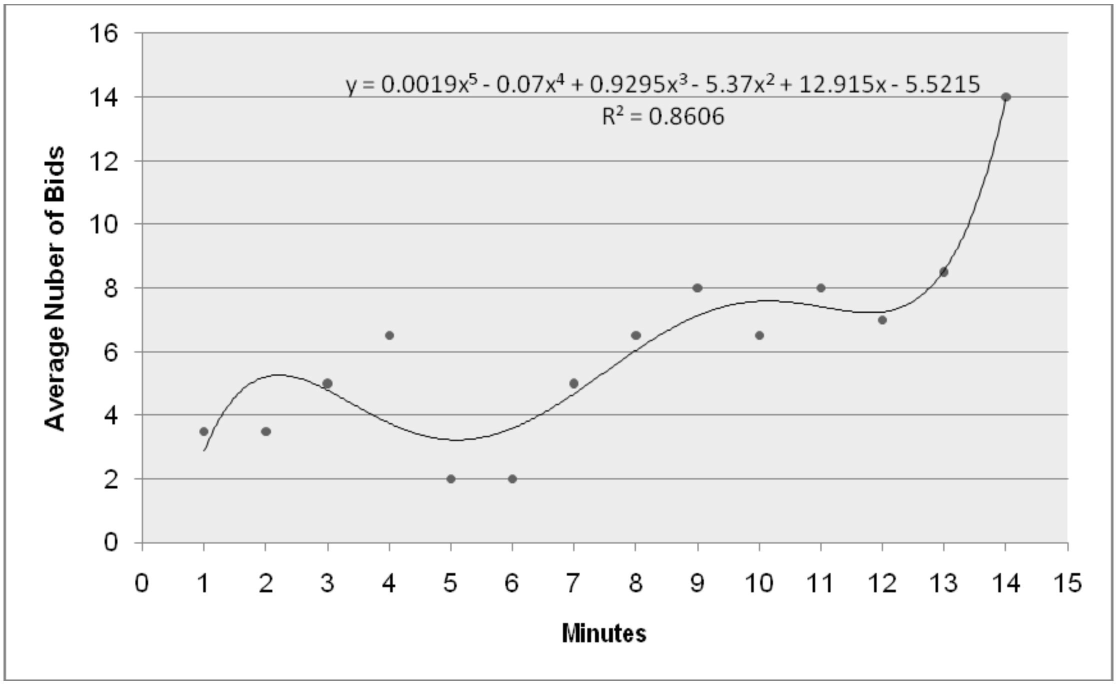


Figure 41 Average Bids per Minute

Figure 41 shows a fifth order polynomial fitted to the data. The clear increase at the last minute of the bidding period is evident. Figure 42 shows the distribution of the number of bids per minute made by Bidder 1. This participant bids at gradually increasing rate with the highest bids at minute nine and fourteen. His bids almost double in the last one minute. Bidder 1 was the third in profit ranking and won 20% of the jobs (6 jobs). A third order polynomial trend line has been used to show the trend.

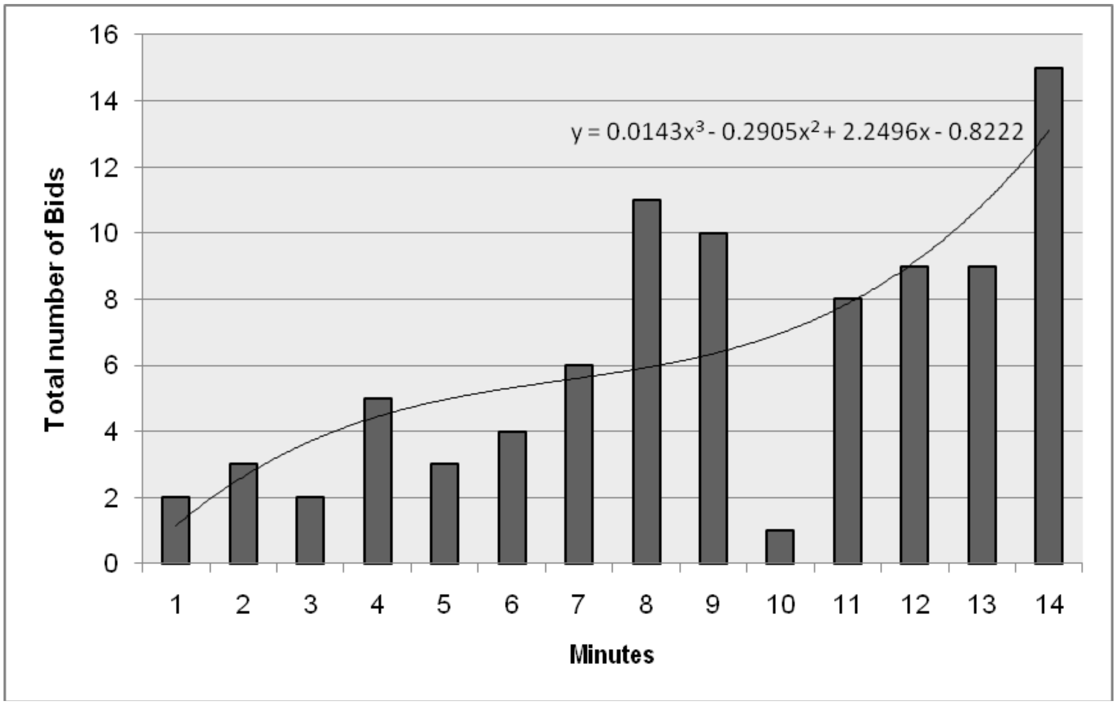


Figure 42 Histogram Showing Bid Distribution per Minute - Bidder 1

Figure 43 shows the distribution of the number of bids per minute made by Bidder 2. This bidder is the most aggressive bidder with the highest number of bids (101). The bidder bids aggressively all through the game and doubles the bids in the last one minute. Bidder 2 was the second in profit ranking, with the highest number of winning jobs that accounted for 40% of the jobs (12 jobs). A third order polynomial trend line has been used to show the trend.

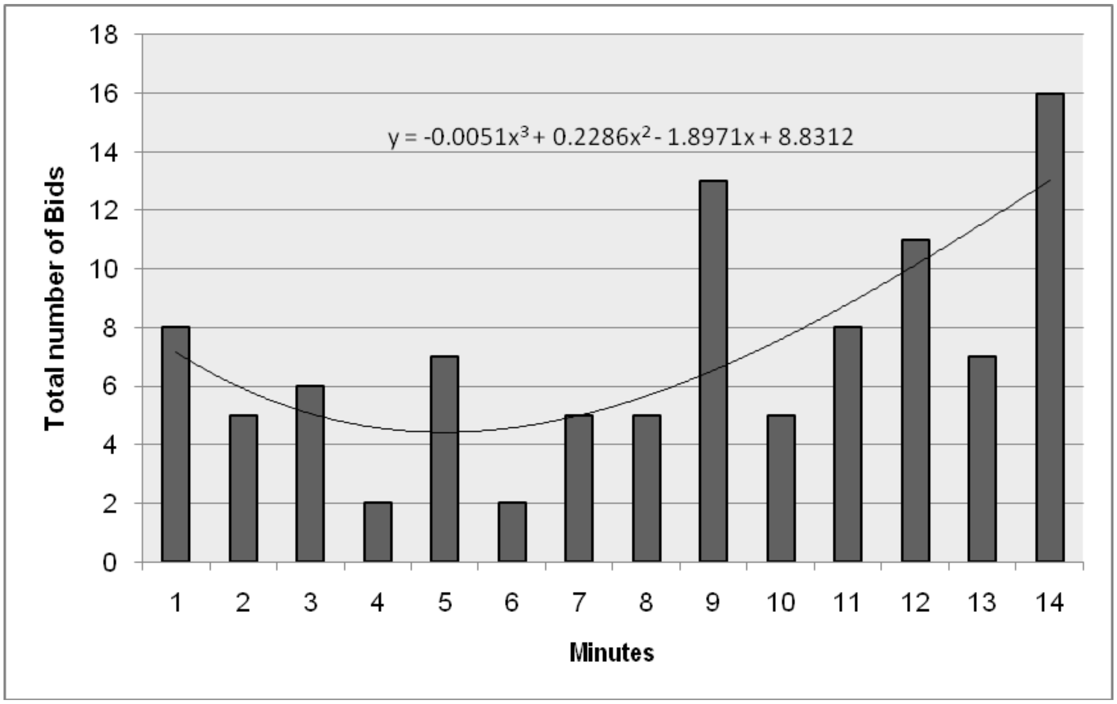


Figure 43 Histogram Showing Bid Distribution per Minute - Bidder 2

Figure 44 shows the distribution of the number of bids per minute made by Bidder 3. This bidder does not bid aggressively until the last minute when bidder 3 almost tripled the number of bids. This bidder was the highest in profit ranking and won 27% of the jobs (8 jobs). This bidder also had the lowest total number of bids. The strategy adopted by this bidder is intriguing and promises to be a future research topic. A third order polynomial trend line has been used to show the trend.

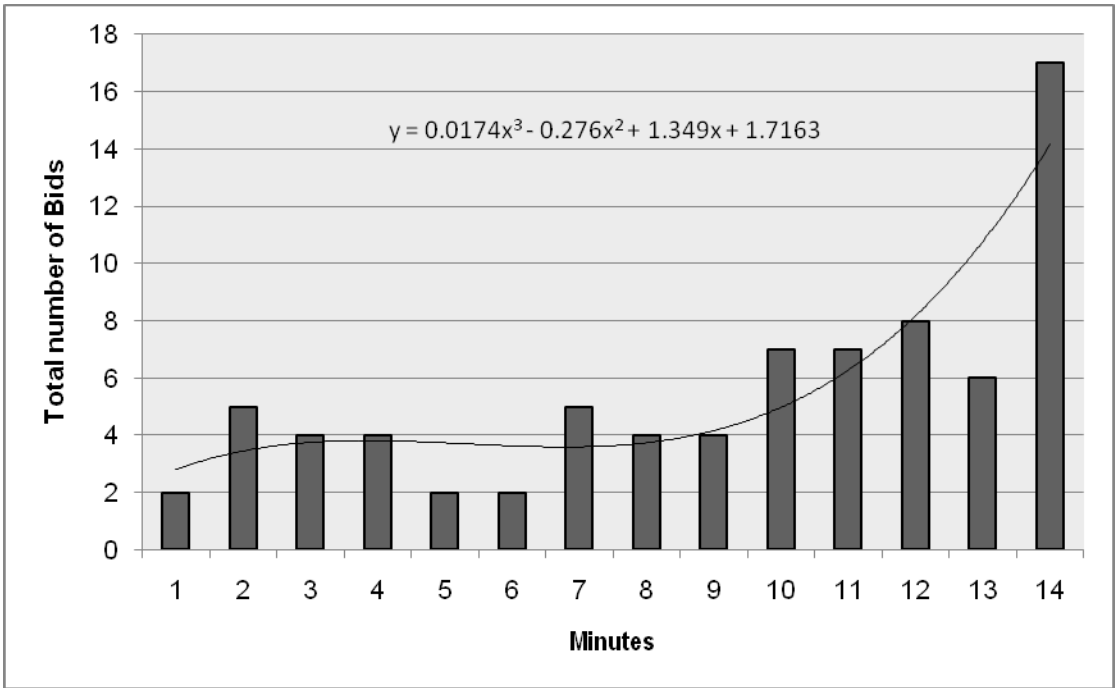


Figure 44 Histogram Showing Bid Distribution per Minute - Bidder 3

Figure 45 shows the distribution of the number of bids per minute made by Bidder 4. This bidder had a somewhat constant rate of bidding. The highest number of bids were recorded in the middle of the bidding period and at the end. This bidder ranked last in profit rankings. This bidder won only four jobs or 13% jobs. A third order polynomial trend line has been used to show the trend.

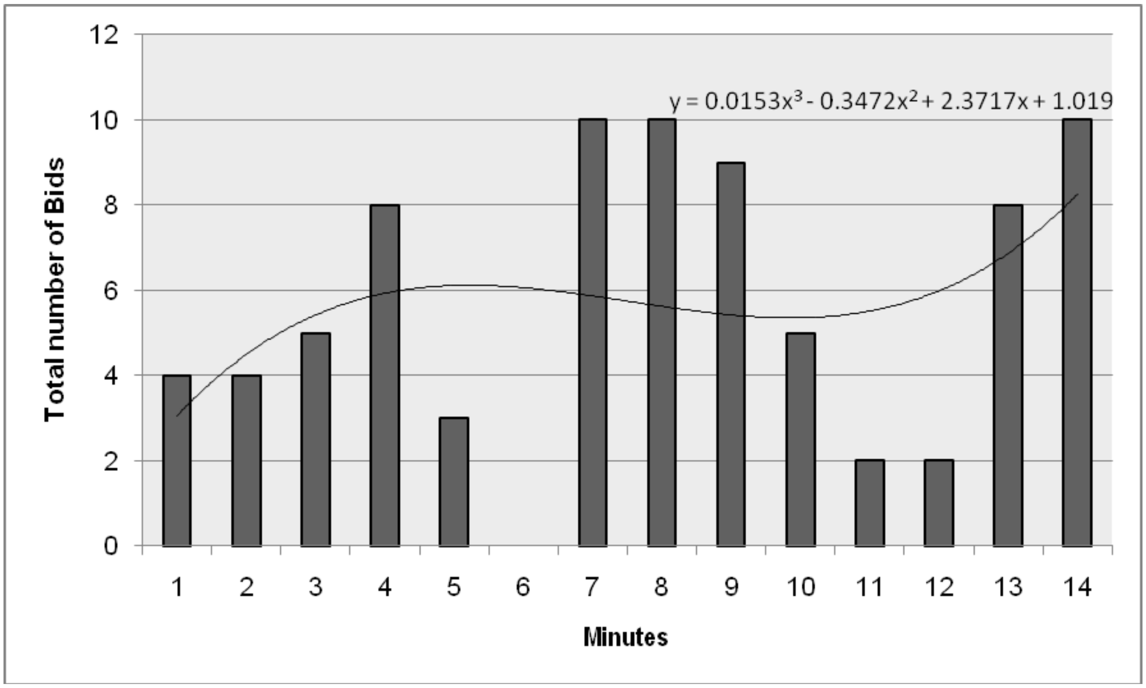


Figure 45 Histogram Showing Bid Distribution per Minute - Bidder 4

From the bid distribution seen in Figures 42 to 45, it can be observed that bidder 3 who obtained the highest in profit, had a steady rate of bidding with the curve sharply rising only in the last minute. Thus, bidder 3 did not lose out money by placing too many bids and made the highest return as compared to all bidders.

In contrast, bidder 2 bid aggressively from the start, continued bidding in the midsection to the end of the bid period. Result was that bidder 2 had the most number of bids, won the most number of jobs, and however this bidder did not make the highest profit as the bidder lost money every time a bid was placed. Comparing the bid distribution from all bidders, it can be said that a successful strategy to maximize returns would be to not bid aggressively at the start, have a low rate of bidding through the bidding period and place the most bids in the last few minutes of the bid period. The same result can be seen from van Vleet's data in the bid distribution analysis of the highest ranking bidder, done by Guhya (2010) shown in Figure 46.

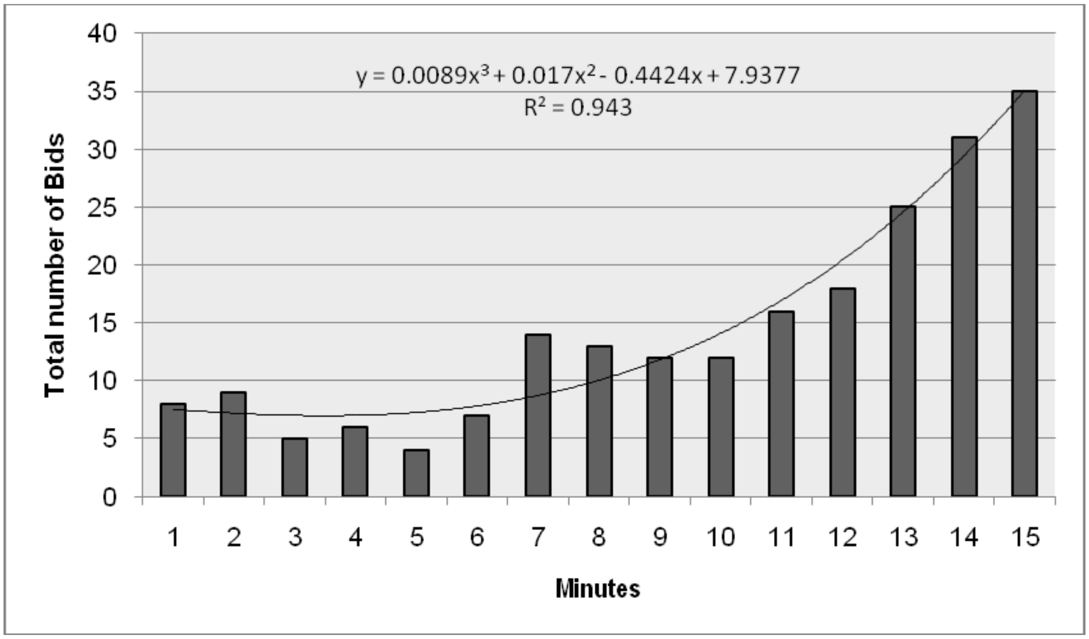


Figure 46 Histogram Showing Bid Distribution per Minute - Highest Ranking Bidder from van Vleet's Case Study

Table 23 presents the data for the trend lines. There does not seem to be any visible relationship between the coefficients and the profit rankings after plotting the coefficients.

Table 23 Coefficients of Third Order Polynomial Trend Line

Ranking	Bidder	Constant	x	x2	x3	Comment
1	3	1.7163	1.349	-0.276	0.0174	Aggressive late
3	2	8.8312	-1.8971	0.2286	-0.0051	Aggressive
2	1	-0.8222	2.2496	-0.2905	0.0143	Aggressive after minute 8
4	4	1.019	2.3717	-0.3472	0.0153	Low rate

DIFFERENTIAL BID DATA

Differential Bid Data corresponds to the price difference between the winning bid and the second last bid (Guhya 2010). Under the rules of the game, a bid lower in price from the current bid even by $1 is an acceptable bid. This fact is often overlooked by the bidders as seen in the data in Tables 24 to 28.

Table 24 Differential Bid Data on All Jobs Won by Bidder 1

Job ID	Price Difference in Lowest 2 Bids
3	0
15	100
18	10
25	0
26	1
42	1

Table 25 Differential Bid Data on All Jobs Won by Bidder 2

Job ID	Price Difference in Lowest 2 Bids ($)
1	1200
5	10000
7	14000
8	0
9	14000
10	400
14	400
16	100
17	15500
24	1
40	499
41	499

Table 26 Differential Bid Data on All Jobs Won by Bidder 3

Job ID	Price Difference in Lowest 2 Bids ($)
2	500
6	0
12	700
13	500
19	0
21	0
22	0
23	0

Table 27 Differential Bid Data on All Jobs Won by Bidder 4

Job ID	Price Difference in Lowest 2 Bids ($)
4	1000
11	100
20	0
27	1

Table 28 Differential Bid Data on All Jobs

	Price Difference in Lowest 2 Bids ($)			
Bidder ID / Job ID	1	2	3	4
1		1200		
2			500	
3	0			
4				1000
5		10000		
6			0	
7		14000		
8		0		
9		14000		
10		400		
11				100
12			700	
13			500	
14		400		
15	100			
16		100		
17		15500		
18	10			
19			0	
20				0
21			0	
22			0	
23			0	
24		1		
25	0			
26	1			
27				1
40		499		
41		499		
42	1			

As implied by the game rules, every subsequent bid had to be lower than the previous bid only by \$1. From Tables 24 to 28, it can be seen that most of the players seem to have overlooked this point. With every lower bid, the players lost money, so to lower a bid by a substantial amount was not necessarily a good strategy for making high profits. Although it might win a bidder more jobs, the bidder would lose profit. In order to win jobs without losing profit, the best strategy would be to lower a bid by the least dollar amount permitted by the game rules; \$1 in this game. The bidder who exploited this rule turned out to make the most profit.

The best example is bidder 2 who lost the most money, won the most number of jobs, but did not make the highest profit. Bidder 3 on the other hand, realized this aspect of the game at the start and as a result made the highest profit. This game winning strategy can also be verified from the data in van Vleet's case study given in Table 29 where bidder 5 was the highest ranking bidder.

Table 29 Differential Bid Data on All Jobs from van Vleet's Data

	Price Difference in Lowest 2 Bids ($)				
Bidder ID / Job ID	1	2	3	4	5
1					149
2	99				
3			1		
4					999
5				250	
6			1		
7					150
8	1				
9			1		
10				299	
11					650
12				25	
13		100			
14	200				
15	50				
16				300	
17		200			
19		68100			
20			67350		
21					1000
22			188000		
23					1000
26			4000		
27		14300			
28				15000	
29	500				
30			5000		
31		76775			
32				14000	
33			3000		
34			4000		

Table 29 continued

	Price Difference in Lowest 2 Bids ($)				
Bidder ID / Job ID	1	2	3	4	5
35	1999				
36		3000			
37					2000
38					1000
39				2000	
40				2000	
41	1000				
42			3000		
43					500
44					500
45					800
46	1999				
47	900				
48				500	
49		1000			
50				500	
51			100		
52			500		
53			1		
54			3500		
55					500
56	500				
57	500				
58			7500		
59			2500		
60					1000
61					5000
62	11000				
63	12000				
64				1999	
65				5500	
66			1000		
67			2500		

Table 29 continued

	Price Difference in Lowest 2 Bids ($)				
Bidder ID / Job ID	1	2	3	4	5
68					100
69		750			
70				5000	
71			6500		
72			7099		
74					1
75	1000				
76					1
77	145				
78	145				

Table 30 looks at the money lost in winning bids by participants in order of their profit rankings.

Table 30 Money Lost in Winning Bids

Ranking	Bidder	Average Money Lost ($)	Std Dev of Money Lost ($)
1	3	213	300
2	2	4717	6520
3	1	19	40
4	4	275	485

It is interesting to note that Bidder 1 lost far less money in winning bids than the rest. Although this bidder ranked third in profit rankings, it is evident that the bidder recognized the fact that winning a job by placing bids whilst not losing money is essential in maintaining higher profits. On the other hand, bidder 2 lost the most money. It is now clear that in spite of winning the maximum number of jobs, 30% more jobs than the second highest bidder in winning jobs, bidder 2 still did not make the most profit. A closer examination of Table 28 confirms these findings.

Figure 47 shows a plot of the data with respect to average number of bids to jobs won. There seems to be an inverse relationship between the average number of bids and jobs won. This can be attributed to the skill of the bidders in recognizing that higher number of bids does not necessarily win jobs, it is a bid at the right moment and right value that makes all the difference. R^2 value of 0.83 is high for the given amount of data related to human performance.

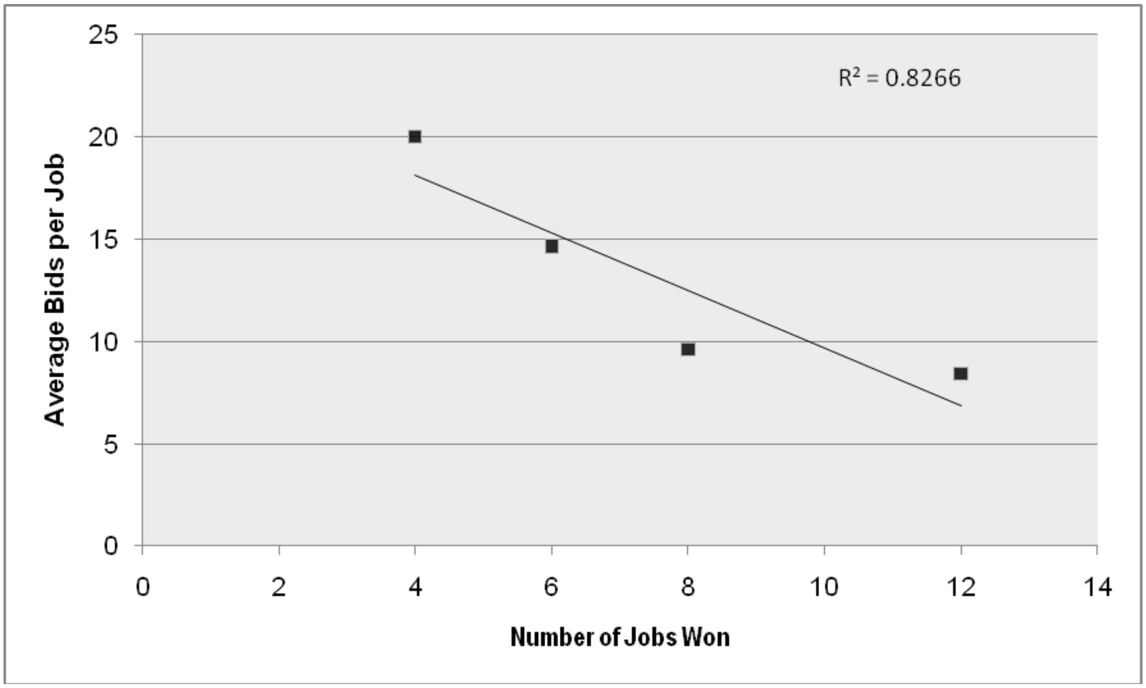


Figure 47 Plot Showing Average Bids per Job to Number of Jobs Won

Figure 48 shows the relationship between the average number of bids made to the amount of profit made by each bidder. This plot also seems to show an inverse relationship between average bids per job to profit earned. The last bidder in profit rankings has the most number of bids. However this could also be caused due to the inconsistency in the data. Investigating this is beyond the scope of this study.

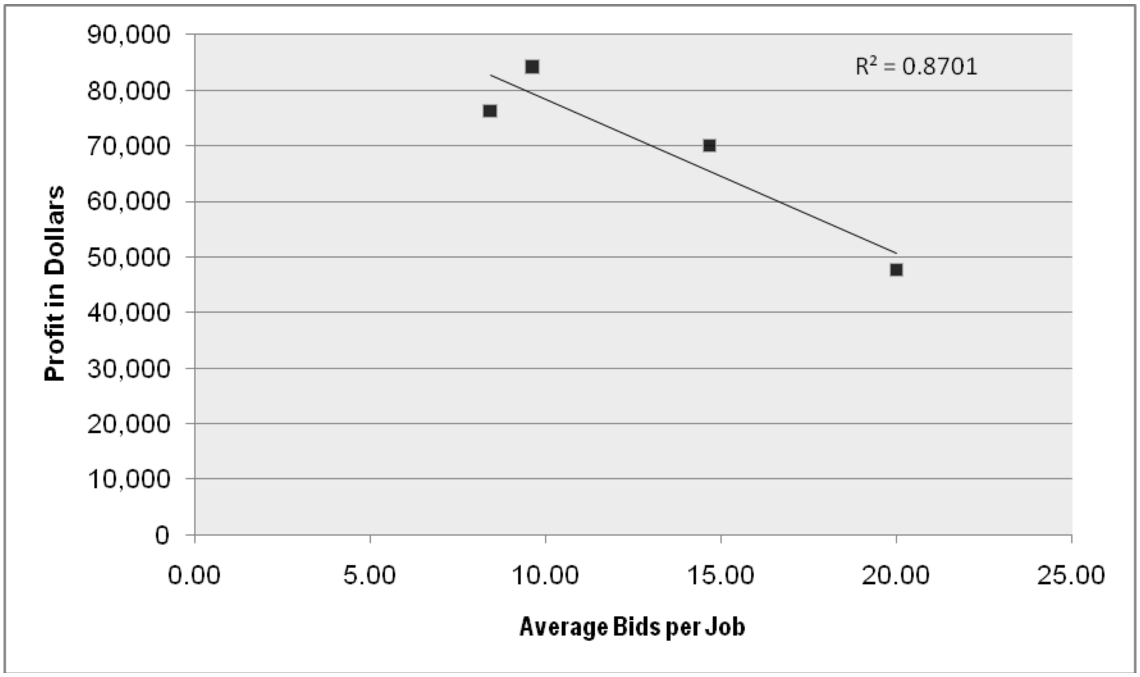


Figure 48 Plot Showing Average Bids per Job to Profit Made

CHAPTER V

ANALYSIS OF THE RESULTS

This chapter reviews the extensive results discussed in the previous chapter. The areas of focus would be the bidding data and patterns. Also the α game and ω game would be examined to confirm the results and probe how they connect to tacit collusion amongst the bidders.

The research objectives for this study are:

1. Establish plots of the bidding data
2. Compare the bidding patterns shown in the plots with time for all bidders
3. Determine if evidence exists in the bidding data to confirm the existence of the ω game and does it represent some form of collusion
4. Compare the returns of the different bidders in the α game to determine if there are any differences in bidding returns and does it represent some form of collusion

Due to the large amount of data in Reverse Auction Bidding studies, identifying patterns and trends in the data is a challenge. Thus this type of study is said to 'Data Rich but Analysis Poor'(Guhya 2010).

BIDDING DATA

The key figures in this study were four bidders who played the game designed by van Vleet. The game was played for a period of five work weeks. The data successfully recorded information on thirty jobs and 346 bids. The job distribution week was determined by a roll of two dice. The total number of outcomes are 36 whose distribution is quite similar to the Gaussian Distribution as shown in Figure 10 (page 33) (Guhya 2010).

The first step into looking for tacit collusion is normalization of the profit made by each bidder given in Figure 19. The histogram of the normalized results is a chief tool in determining the driving force behind the competition and game α. In order to look further for tacit collusion, the more able bidders whose average return or profit is higher than the rest, should be observed.

BIDDING PATTERNS

The four distinct bidding patterns in the learning curve of bidders new to the game of Reverse Auction Bidding were put forward by Chauhan (2009). The presence of the bidding patterns was confirmed in Gujarathi's data by performing a Student's t-test. However when the results were compared with van Vleet's data from 2004, the comparison was not quite the same pattern. The reason behind this could be investigated in future studies.

There are many interesting findings in the study that need further evaluation

- such as the inverse relationship between number of bids per job to the number of jobs won
- the inverse relationship between the average number of bids per job to the profit made is exactly the opposite what would be expected out of a study in bidding.

The player who had the highest profit efficiency also had the lowest amount of returns and won the least number of jobs. What were this bidder's strategies that lead the bidder to gain highest returns on the jobs won but ultimately landing the bidder at bottom of the rankings for return on investment. Return on investment is a key indicator of economic ability.

On the other hand, the bidder who placed the maximum number of bids also won the most number of jobs. However the bidder profit efficiency was the lowest amongst all while the bidder's profit ranking was 2.

Results coming from the differential bid data in Table 28 show the presence of canny players who learned the principle of maintaining higher levels of return very early in the game and beat the competition early. It is one of the indicators of the α game. The profit percentages are highly varied amongst the bidders over time and this confirms the presence of the ω game.

GAME ω

The basic concept of a Reverse Auction is to minimize the average costs of goods or services to the υ player. The υ player sets the rules of the game and has to accept bids that fall within those rules. The only way to judge the success of the process is the average cost of the job that the υ player has to settle with.

Although a Reverse Auction promises in some ways to be an economically better alternative to the widely used hard-bid system, professionals in the construction industry are skeptical about its use, one of the reasons being tacit collusion that obliterates the main motive of the υ player. The presence of two sub-games in the Reverse Auction Bidding game, termed as the ω game and α game was postulated by Nichols (2010). The ω game is played between the bidders (λ_i player) and the υ player whereas the α game is a multiplayer game between the λ players.

In all the Reverse Auction Bidding studies conducted at Texas A&M University, there is no evidence that the υ player is able to succeed in reducing the average costs. The same was demonstrated in this study with all players gaining high profit levels even with the competition.

GAME α

In this sub-game, the λ_i players are playing between them with an intention to maximize their average returns. The results of this study show that some players are able to gain much higher returns as compared to their competitors over the period of time. Since the first study completed by van Vleet in 2004, many consequent studies have tried to address this issue and determine the cause.

Analysis of Gujarathi's case study has suggested that the α game begins when a λ_i player places a bid on a job. After the bid is placed, there are two possibilities:

1. The λ_i player will not face any competition; the bid will remain in the system until the set time ends and the λ_i player will win the job.
2. The initial bid will be undercut by another bidder. There are three possible scenarios after that:
    a) The bid will be undercut by the minimum offered limit of the game ($1 in this case)

b) The bid will be undercut by a significantly higher amount than the offered limit of the game (in the case of job ID 17, the winning bid cut the second lowest bid by $15,500)

c) The subsequent bid will be lower than the cost of executing the job

In case of the first possibility, this is the ideal case for the λ_i players as it maximizes this bidder's return. However it is the worst scenario for the υ player as it will offer the purchaser the highest cost. These possibilities have occurred in Gujarathi's study in Job IDs 6, 19 to 23 and 25 where the initial offered high price bid was never undercut.

In case of possibility 2a, here the α game really becomes a two player game. This strategy is best in terms of the λ_i players as it helps to keep their returns high while being under the rules of the game. The υ player again clearly loses the game. Gujarathi's data shows how the bidders missed this point initially in the game, but learnt it soon to gain consistent high profits. Job IDs 24, 26, 27 and 42 demonstrate this case.

In case of possibility 2b, the λ_i players are clearly losing out on the game rules. Even though 2a is in their best economic interest, the occurrence of 2b is more prevalent than 2a. The study shows that 2b takes place in the initial game play when all the bidders have no prior experience with Reverse Auction Bidding. As they get past their learning curve, their game shifts from 2b to 2a. Table 26 shows this case.

The occurrence of 2c is only possible when the λ_i player makes a mistake or clerical error on the bid. This case has been documented on previous studies done on

Reverse Auction Bidding. However this can be controlled by setting the rules on the game.

CHAPTER VI

CONCLUSIONS

The Reverse Auction case study completed by Gujarathi in 2008 reveals intriguing characteristics of the Reverse Auction game. The game was conducted using the same website developed by van Vleet (2004), who used an ASP and Microsoft Access database to record the game. This study has statistically analyzed the data recorded in Gujarathi's case study and examined the bidding patterns and bidding behavior of the participants.

The game scenario was developed by van Vleet where each job was to construct a slab for a home builder. There were four bidders in this game and each had a capacity to undertake three jobs per week. They also had an option to increase their capacity by paying fees to a bank. The construction took place over six sites around the Houston TX area. The game recorded five weeks of bidding activity, with a total of thirty jobs and three hundred and forty six bids. The details of the statistical analysis are given in the results chapter of this study. It is concluded the presence of two different games in the Reverse Auction system can clarify the tacit collusion that is observed in the players of the game.

The ω game, the first game, is the real objective function of the Reverse Auction system. This game is a two player game between the purchaser (υ player) and the set of bidders (λ_i players). The intention of this game is to lower the average cost of jobs for the purchaser, as it is the purchaser that creates and operates the game. The purchaser wins the game by creating economic pressure on the bidders and getting the lowest bids to complete the jobs, thus saving the purchaser on total costs.

However, the bidders can win this game by increasing the average cost of jobs, thus maximizing their overall returns. The study shows that under the rules of the game, able bidders can gain higher profits.

The α game is the second game and more implicit game. It is multiplayer game played amongst the bidders (λ_i players). It is this game that provides a huge profit making opportunity to the canny bidders. The bidders are competing with each other to maximize their profits and gain an economic advantage over the other bidders. By taking advantage of the game play strategy as explained in the analysis of results chapter, the bidders can gain increased returns that put them ahead from the other bidders.

Thus the common conception that Reverse Auction Bidding systems reduce the costs for the purchaser as compared to hard bid system, is probably wrong. Under the rules set in this game, some bidders were able to achieve higher than average results.

The study also puts worth a future area of research in developing the game in ways that the tacit collusion can be eliminated, minimized or controlled in some form by the purchaser so that the true motive of getting lower costs can be achieved for the bidder.

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